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An Empirical Analysis of the Contagion Risk in the Stock Markets: Evidence with E-GARCH VaR Model

by

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MSc Risk Management

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ABSTRACT

This paper examines contagion risk among both current Eurozone Crisis and Asian Crisis in 1997 with daily stock prices during the crisis periods. Three types of financial markets are included to check the risk spillover, which are developed countries (G7 group), emerging countries (BRICs countries) and benchmark countries (Spain, Portugal, Greece and Ireland for Eurozone Crisis, while Indonesia, South Korea and Thailand for Asian Crisis). E-GARCH (1, 1) VaR model with Generalized Error Distribution (GED) is applied for each stock index for evaluating the volatility. Also, Granger Causality test is used to check whether there exists risk spillover. It is found that there is statistically significant evidence of contagion effect contagion risk among both current Eurozone Crisis and Asian Crisis.

Keywords

Contagion Risk; E-GARCH Modelling; Value-at-Risk (VaR); Backtesting; Granger Causality in Risk

1. INTRODUCTION

In the recent decades, global markets are interacted increasingly through close financial links. When a financial crisis happens, it would hard-hit the banking system by rapidly transmitting from one market to another and finally arriving at the global markets. This phenomenon has become significant, especially for recent financial crises.

A great deal of practical studies have concerned on the probability of market movements. Large market movements can be resulted in various reasons, such as policy changes, uncertain future, terrorist attacks, and risk spillover from other markets (Hendricks et al., 2007). These extreme negative events may cause large capital movements among the markets. Global financial markets have interactions and inter-linkages with capital movements. When negative downside event comes, interactions and inter-linkages would bring the risk spillover to correlated markets through the capital movements. The US sub-prime mortgage market crisis happened at the end of 2007, and it swept the banking system and quickly transmitted to the global financial markets. The effects of the crisis were automatically reflected in the rest of the world economies (Rigobon, 2002). Current Eurozone Crisis also supports the argument that the outbreak of the Greek financial crisis caused the large market movements of other European countries. Hence, it is necessary to identify whether current Eurozone debt crisis shows contagion or interdependent effect on the stock markets. If there does exist contagion effect, how the contagion risk spread and influence different markets would be an interesting topic to explore. Furthermore, if the financial crisis occurred in emerging markets and spread to developed markets, studying whether the contagion risk still has the same magnitude could help to make risk management to avoid contagion risk in different markets.

Regardless of concern over the recent financial crises, rare studies have analysed contagion risk among both developed countries and developing countries (Blundell-Wignall and Slovik, 2011). The difference in financial markets may lead to uncertain results on contagion effect. Hong et al. (2004) illustrate the how specific market shifts are transmitted to other countries in the stock markets that their study focuses on the contagion risk between Chinese, American and German stock markets. In this dissertation, several questions would be studied. The existing literature presents a number of insignificant evidences on contagion risk among financial crisis (Dungey et al., 2005). Hence, whether stock markets show contagion or interdependence effects across countries is the first question to study, during the current Eurozone debt crisis in 2010. Additionally, the spreading way of contagion risk is worth paying attentions as well, which would help to understand the mechanism of risk spillover to better financial risk management. Then, it is interesting to check whether the developed countries would suffer the same contagion effect compared with emerging markets. Also, comparing with Asian financial crisis in 1998, this paper will research whether the contagion risk still make the same effects if the financial crisis occurred in emerging markets and spread to developed markets. At last, the research of risk causality in stock markets could provide new method for risk management.

Based on current positions, Value-at-Risk (VaR) is selected to measure the risk. Jorion (2010) suggests that VaR has become a widely applied statistical approach to measure different risks. In this paper, two parts of empirical practices are presented, which are Eurozone Crisis and Asian Crisis. Three groups of samples comprise this research that developed countries (G7 group), emerging markets (BRICs countries) and benchmark countries (Spain, Portugal and Greece for Eurozone crisis in 2010, while Indonesia, Korea and Thailand for Asian financial crisis in 1998). E-GARCH (1, 1) VaR model with Generalized Error Distribution (GED) is applied to accommodate the samples to generate the contagion effect. Besides modelling the contagion risk, model validation is conducted by Unconditional Coverage Test (Kupiec) as well as Conditional Coverage Test (Christoffersen) to check if the selected model and distribution could fit all the samples. At last, Granger Causality Test will examine whether there exists contagion effect among the markets.

In general, emerging market group is expected to more likely to be affected by the benchmark volatility than developed country group, due to the advanced financial system would protect developed countries themselves from the extreme downside shocks, but the developing countries might lack the financial strategy to defend the crisis. For this reason, an effective financial system seems to be very meaningful. A key point of this study is to detect whether there exists regional effect within the benchmark groups, where regional markets with co-movements would affect or interact with others significantly in the benchmark groups.

This study has identified significant contagion effects in the Eurozone Crisis as well as Asian Crisis. However, the results have some differences. There is strong evidence of contagion effect in the Eurozone Crisis. Indeed, emerging market group is more likely to be affected by the originator, which is the same as the assumption. However, developed and developing group in the Asian Crisis shows weak evidence for contagion risk, but the risk spillover in the benchmark group is significant. As a consequence, this study has found significant proof in the both crises that contagion risk does exist and spread when the extreme negative events come, and given explanation for this phenomenon

The structure of this study is to review the literature on the correlated topics firstly. Then, methodology will be followed to construct the model for measuring the risk. Empirical analysis contains both Eurozone Crisis and Asian Crisis part. Further discussion will explain the questions mentioned before. Finally, conclusion and some suggestions would be given for further studies.

2. LITERATURE REVIEW

2.1 Contagion Risk

Contagion risk defined as significant economic changes, in other words as market risks, would spread from one country to other countries. According to the definition of contagion, perhaps the best explanation comes from Dornbusch et al. (2000). They emphasize that contagion effect shows apparent increase in the cross market co-movement when a financial market suffers the negative shifts, and the asset prices or financial flows would move together within the markets correlated to this co-movement in a particular period. However, this presentation is under argument that risk spillover can be assessed easily by the presence (or absence) of mechanisms of actions to protect markets (Morales and Andreosso-O'Callaghanb, 2012). Markwat et al. (2009) describe stock market contagion risk as a domino effect, where the local crisis would interact with external events to become more serious crashes. Baur and Schulze (2005) refer contagion as the specific co-exceed data, which could not be explained by the covariates with different quantiles. Generally, contagion could transfer either economic booms or economic crises throughout a geographic region. With the globalization of the economy in recent decades, this phenomenon appears in many financial crises increasingly, especially during the 2008 global financial crisis period. As a result, it is necessary to investigate the contagion effects among various countries. Understanding these effects would contribute to identify future trends of international financial markets and help the government to make polices.

Usually, individual country integrates into the global financial markets by involving financial links like trades, forward and future contracts, options and derivatives. There are three main types for contagion links, such like trade links, financial links and competitive devaluations (Dornbusch et al., 2000). Furthermore, Allen and Gale (2000) identify that institutional linkages could pass the contagion effect. Dornbusch et al. (2000) emphasize both trading and financial links transmit the risk spillover by identifying contagion risk in the selected countries. A financial crisis which occurs in one country could make financial effects exposure to the abroad by these links. More recently, some studies have pay attention to the linkages within international banking system due to the system could transmit the risk spillover to other financial institutions. If a financial crisis spread one market to another, these economies would be dragged into a downward spiral (Diebold and Yilmaz, 2012).

Dungey and Martin (2007) introduce an empirical model to study the linkages between currency and equity markets of Asian Crisis in 1997. They provide statistically strong evidence on both spillover and contagion effects, since cross-market links are important to transmit the negative downside events. Consequently, the speed and scale of spreading contagion risk depends on the degree of the integration. The significance of the contagion effects would increase with the degree of integration (Chudik and Fratzscher, 2011). It can be argued that financial markets facilitate the spreading of real or common negative events. However, it is not the reason for contagion effect. Hence, to analysis contagion and interdependent effect of different financial market is very importance when suffering shocks.

Financial crisis could be linked to internal economic weaknesses, as well as external shocks. The factors could be diverse, such as interest rate shocks, sudden reversal of capital flows, wars and so on. In a short time, the crisis would spillover to other markets due to regional integration or market interaction (Khalid and Kawai, 2003). As a result, a financial crisis, which happens in a specific country, could be attributed to various factors and spread to the correlated markets. One typical example is the Asian financial crisis from 1997 to 1999, which swept across Asian countries and caused huge loss.

Some studies argue that contagion risk could be apparent with cross-market linkages when an individual country or several countries would suffer a financial crisis (Dornbusch et al., 2000). For example, the financial crisis in 2008 has swept the globe quickly. Iwatsubo and Inagaki (2007) give the evidence of significant contagion effects from the US market to the Asian. They find that as the headstream of this crisis, US market influence the transmission of information largely to foreign markets, in which the intensity of contagion shows greater significance during the crisis than after the crisis. Conversely, some opinions suggest that the sudden shifts, rather than the correlation increasing, in market expectations and confidence determine the contagion (Corsetti et al., 1999). Dungey et al. (2005) support this argument that they research the co-movements in the equity markets of both Asia and Australia, which are mostly decided by interdependent linkages arising from common systemic factors. Though negative shifts produce more effects than positive ones, contagion effect is still insignificant (Menezes et al., 2006). Bae et al. (2003) emphasize that normal common factors and linkages between financial markets should be taken account into consideration before modelling the volatility of crisis. Other studies illustrate the similar arguments of contagious effect (Bekaert et al., 2005). On the other hand, contagion effect addresses the unexplained and unexpected negative downside events. Each financial market interacts with the global markets through financial links. If a financial crisis occurs in a country, trading would decrease sharply and investing capital would flow abroad. Hence, the scale of contagion effect would hinge on the degree of financial market integration. The higher the degree of integration, the more serious the risk spillover is (Dungey et al., 2010a). Besides the arguments, some studies show that heteroskedasticity on correlation coefficients would give conditional correlation coefficients of the volatility (Forbes and Rigobon, 2002), which leads the results to be biased. In other words, the independent results reflected by the tests are before the crisis but not the fact during the crisis. Similar findings can be seen in many other studies (Araujo and Garcia, 2013; Baur, 2012).

Another famous example of contagion effect is Asian financial crisis in 1997. It started with failure in the currency markets of Thailand, since the Thailand government determined to no longer peg the local currency to American dollar. As a consequence, currency devaluations rapidly transferred across South Asia, which came with decreasing in stock markets, declines in import revenues and even government upheaval in the summer of 1997 (Baig and Goldfajn, 1999). Comparing with high growth performances before, many countries were facing a recession. They had to invite the International Monetary Fund (IMF) to help them get out of recessionary pressures in the economies, as their domestic policies failed to respond to negative shifts. Although the Asian Financial Crisis was stemmed by financial intervention from the IMF and the World Bank, declines were inescapable across the global markets as the Asian economies slumped (Baig and Goldfajn, 1999). In this financial crisis, Indonesia, South Korea and Thailand suffered the most effects.

Contagion risk is considered to be the most important factor that Thailand transferred its shocks to other countries and caused the crisis. Some researchers point out that contagion risk is transferred by the channel of strong trades and financial linkages (Forbes and Rigobon, 2001). Actually, the crisis seems to have contagion effects immediately on the neighbours in Asia at the beginning, after which it spilt over the global markets by the end of 1998. Nevertheless, it provides a testable hypothesis whether contagion risk or a consequence of common factors affecting the regional economies.

2.2 Measure the Contagion Effect

Many empirical studies aim to build models on contagion effect by measuring the changes in the relationships between the different capital markets. Forbes and Rigobon (2002) illustrate that the correlation coefficients are conditional on market volatility. They find significant market co-movements in the financial crises but these co-movements are viewed as interdependence before. The increased scale of existing linkages brings the contagion effect to other markets. Dungey et al. (2005) also emphasize that risk spillover could be regarded as new channels which open the ways to transmit the negative downside events. Bae et al. (2005) indicate that it is important to separate tranquil and crisis periods to research contagion effect by building threshold models. Markwat et al. (2009) apply ordered Logit regression to measure the local, regional and global events, which addresses that the global negative shifts are cumulated by local and regional extreme downside shocks.

Regional market return and volatility determine the contagion, especially for extreme negative returns than for positive ones (Baur and Fry, 2009). Morgan (1994) first launched Risk Metrics system with the popularity of VaR. Morgan (1996) has developed methodologies for using Value-at-Risk (VaR) into a portfolio of financial instruments, as well as a detailed description of Risk Metrics and a benchmark for market risk measurement. Value-at-Risk (VaR), which defines as p% of loss, is a widely used measurement in risk management (Beder, 1995). As for VaR, it gives probabilities with specific loss amount, which is simple to understand and relatively easy to back-testing. After Morgan (1994; 1996), the trend of studying the validation of the underlying statistical assumptions has increased. Why researchers interest in VaR is that it reflects each point of the tails estimated in empirical data (Angelidis et al., 2004). Additionally, VaR measures risk factors in a consistent way. It enables that the risk is assessed as a whole of portfolio risk (Hull, 2012). In other words, it has taken account of risk interaction with each other at the firm wide level. This explains the reason that VaR is widely used as in the financial markets (Fan et al., 2008).

Hendricks (1996) generates three VaR models for the foreign exchange markets, while he also has tested twelve VaR assumption of normality. Nine criteria are used to evaluate model performance, but none of the assumptions shows superior performance. Then, Danielson (2003) proposes different VaR models as risk measures from both internal and external (regulatory) points of view. He demonstrates that the VaR measure may give misleading results which might even increase systemic risk. Similarly, Culp et al. (1998) state the weakness in existing VaR approaches.

Venkataraman (1997) also estimates VaR values based on both the assumption of normality and the mixture of normal approach in the foreign exchange markets. Considering the traditional normality approach producing much more violations of VaR significantly than the mixture of normal approaches, the mixture of normal assumption has a better performance than the traditional normality assumption. They conclude that mixture of normal approach could account for fat-tailed data, which is a tractable approach to VaR. Particularly, Tsay (2005) analyses VaR calculation methods of stock market with both parametric (including extreme value theory) and non-parametric approaches. Some studies address that rare extreme events should model VaR with both unconditional and conditional concepts of extreme values, which could help to understand the risk measure (Hendricks, 1996).

The study of Angelidis and Degiannakis (2007) covers stock exchanges, commodities, and exchange rates. In their research, VaR models are estimated with ARCH volatility specifications that the performance of different distributions for VaR would be compared after the estimation. Moreover, they propose back-testing procedure to forecast with different model and to select optimal model for each financial market. The most interesting finding of their study is that there exist a small amount of models which could generate the VaR accurately for both long and short periods. However, the flexible models do not equal to accuracy. It depends on the assumptions of distribution and volatility specification. Their study provides a comprehensive presentation of the measurement and applications of VaR (Angelidis and Degiannakis, 2007). Also, Hoppe (1998) has studied stock, bond, and exchange markets by using VaR models and found that variance-based statistical methods seems to interact among trailing sample length and holding period. The study suggests that a short length of sample size could reflect changes better than a larger sample size (Hoppe, 1998), which provides more accurate VaR values, since sample with long period might lower the VaR values (Frey and Michaud, 1997).

Many studies hold the same assumption for applying VaR that asset returns follow normal distribution, which is simplifying the computation of VaR considerably. However, there are sufficient empirical evidences showing the incoherent results with this hypothesis. Moreover, some data even reflect fat tails in distribution, which violates the hypothesis of normal distribution (Jorion, 2006). According to normally distributed assumption, it could not predict extreme events accurately if the events are more possible to occur in practice. Therefore, inconsistent measures of the risks in practice are totally inappropriate.

Thus, to choose appropriate distribution and volatility specification is very important for using VaR to measure extreme market risk. When appropriate models are determined, VaR in one market could help to forecast the current or future risk in another market.

2.3 E-GARCH Model

There are many empirical studies for testing that whether has contagion effect during financial crises, but none of theoretical or empirical procedures are accepted by most researchers (Morales and Andreosso-O'Callaghanb, 2012). VAR (Vector Auto-Regression) model is a potential alternative for testing contagion effect (Enders, 2008). Other methodologies include correlation analysis (Forbes and Rigobon, 2002) and probability theory (Eichengreen et al., 1995). Certainly, some studies use GARCH or GARCH family model (T-GARCH, E-GARCH, I-GARCH and so on), such like Araujo and Garcia (2013), which proposes good results on testing contagion risk.

Considering asymmetric and non-normal distribution, Billio and Pelizzon (2000) estimate the VaR of a switching volatility model to predict the distribution of returns. In this study, estimated VaR results are compared with variance-covariance (VCOV) approach and GARCH (1, 1) model. They prove that the calculated VaR with switching volatility model has a better performance than other methods. A compatible alternative distribution is skewed Student distribution. Some studies (Giot and Laurent, 2003) introduce skewed Student distribution into VaR models, which performed better than other alternatives. For skewed Student distribution, numerical optimization procedure is not required in estimating models, which shows superior property than other distributions.

The methods calculated VaR values include Historical Simulation, variance-covariance (VCOV), Monte Carlo Simulation methods and so on. Vlaar (2000) tests these different approaches for determining an adequate VaR model for samples. The results (Vlaar, 2000) show that although GARCH-like variance specification is satisfied, the model would underestimate real variance and lead to too much exceeding errors. However, results could be improved when applying a combined model with variance-covariance (VCOV) and Monte Carlo Simulation method with normal distribution, which under GARCH specification. Angelidis et al. (2004) select five stock markets (S&P500, NIKKEI225, FTSE100, CAC40 and DAX 30) to test the performance of an extensive family of ARCH models. In this study, daily VaR values of perfectly diversified portfolios are produced to test several distribution assumptions and sample sizes. The results indicate that different portfolios would require different models to forecast the VaR values accurately. Therefore, arranging a suitable model with appropriate distribution and sample size to forecast volatility is the first thing to be considered. Another piece of evidence is from the research of Angelidis and Degiannakis (2007). They suggest standard normal or GED for the most appropriate to calculate risk measures based on ARCH volatility models. For most financial portfolios, asymmetric volatility models would be better than symmetric ones.

Billio and Pelizzon (2000) apply the volatility models to calculate VaR values, which are compared with the Variance-Covariance (VCOV) approach GARCH (1, 1) models. They also backtest the VaR values that it is obvious the regime beta model shows superiority than other methods. Many empirical studies support this statement that Frey and Michaud (1997) fit different GARCH models to find that the distributions corresponding to the models allowing for an asymmetric reaction of volatility to return shocks have considerably more mass in the lower tail than those of the symmetric models. This is reflected in prices and payoff distributions of derivatives. Other studies have proved that there exists risk spillover when suffering the financial crises. Giot and Laurent (2003) compare stock performances with the Risk Metrics, Normal APARCH, Student APARCH and Skewed Student APARCH models. The judgment is based on the estimated VaR results. At last, they address that an AR-APARCH model combined with a Skewed Student-t distribution performs very well.

Dungey et al. (2010b) applied an identified structural GARCH model to simulate the dynamic financial crises due to the structural GARCH model could track the potential independent shifts to distinguish different transmissions in the capital markets. They draw the hypersensitivity of a domestic market out of financial crisis in terms of the news from foreign non-crisis markets, as well as the risk spillover coming from foreign domestic market within the crises. Apparent evidence of hypersensitivity has been identified, while the contagion phenomenon is also significant.

In order to fix the shortcoming of GARCH model, Nelson (1991) has proposed a new model to fit the asymmetric information in the empirical data, which is the exponential general autoregressive conditional heteroskedastic model (E-GARCH). Yang and Doong (2004) apply this model under a multivariate way to evaluate asymmetries in the volatility transmission mechanism where the research targets are stock prices and exchange rates. They state that a direct effect of exchange rate changes reflects on future changes of stock prices. Aloui (2007) has employed the same model to find that movements of stock prices influence exchange rate dynamics. Although a range of different methodologies have been presented to analyse contagion effects, E-GARCH model shows its superiority in analysis. There are several studies (Aloui, 2007) which use the E-GARCH model to capture the volatility of stock returns, especially for the asymmetry in stock market volatility. The E-GARCH model has several strengths than other models. To begin with, the E-GARCH model is free of nonnegative constraints on the parameters, which impose such restrictions for GARCH model. Also, the E-GARCH model can successfully capture the asymmetric volatility in the stock market.

2.4 Backtesting

It is not enough to just estimate the model for prediction, but also needs to examine the model validation whether the model gives the adequate prediction (Jorion, 2006). Since the forecasts rely heavily on the estimates, small bias in the modelling process, such as misspecification, under-estimation of tail risks and so on, might cause large failure in the forecasts, so backtesting plays a critical role in the risk measurement.

The early idea of backtesting follows the Bernoulli sequence, which is a basic frequency test (Jorion, 2009). In order to cover the shortcoming, Kupiec (1995) introduces Unconditional Coverage Test (Kupiec) for backtest the values of VaR. Moreover, Christoffersen (1998) has developed Unconditional Coverage Test (Kupiec) into Conditional Coverage Test (Christoffersen), which captures both the frequency and independence of exceptions (Campbell, 2005).

Previous studies have shown the superiority of backtesting. Angelidis and Degiannakis (2007) compare different models for estimating VaR values. The models are examined by a two-stage backtesting procedure that only several models can predict the VaR values for both long and short trading positions accurately. Another study is from Araujo and Garcia (2013) that they select the best model for forecast different stock indices by backtesting. Indeed, the backtesting method does help to correct the model. They have found significant evidence of contagion effect among the European stock markets.

In order to make adequate VaR values, both Unconditional Coverage Test (Kupiec) and

Conditional Coverage Test (Christoffersen) are introduced into this paper.

2.5 Granger Causality

The aim of this study is to detect the contagion risk within the financial crises. As a consequence, there should be an approach to examine the risk spillover of the extreme downside events among the stock markets. Therefore, Granger Causality Test is introduced into the studies of contagion effects to test the relationship between two time series (Hong, 2001). Granger (1969) has developed the Granger Causality Test firstly into the analysis. It is a statistical hypothesis test to check whether the selected time series can be the reason to influence another time series (Granger, 1988). In other words, applying the historical data of one time series could contribute to forecast the parameters of another time series in the future. When this relationship is significant, the former time series can be viewed as the Granger Cause of the latter time series.

Studying the volatility spillover between Deutschemark and Japanese yen, Hong (2001) states that changing in past Deutschemark volatility Granger causes a change in current Japanese yen volatility, but in contrast, no significant Granger Causality is revealed. Additionally, Alagidede et al. (2011) have proposed a study into the co-interaction between the stock markets and foreign exchange markets. They select the samples from Australia, Canada, Japan, Switzerland, and UK to carry on this study. Unlike the previous researches that find no evidence of long-run relationship between the stock markets and foreign exchange markets, Alagidede et al. (2011) have figured out the strong evidence of co-interaction from exchange rates to stock prices, whereas the Swiss sample reflects insignificant co-interaction. Hong et al. (2004) develop the concept of Granger Causality tests in analysing the spillover on the extreme negative shocks of the Chinese stock market. In addition, they discuss the effect between the Chinese stock market and other international stock markets as well. There are strong risk spillover within Chinese stocks, between stocks of Chinese mainland and other regions (such as Hong Kong and Taiwan), and Chinese stock market several South Asian countries, while insignificant spillover effect exists between share A indices and major international stock markets. In contrast, share B index and particularly share H index reflect most extreme downside contagion effects from international stock markets.

Following the approach of Granger Causality Test in risk (Hong et al., 2009), Fan et al. (2008) set GARCH models to calculate VaR values of international crude oil price returns. This study mainly applies Generalized Error Distribution. Note that back-testing approach of Kupiec (1995) is also included in evaluating the models. Similar to other previous researches, negative shocks always show spillover effect, while positive ones do not have the same performance. Historical information on risk could promote to predict future extreme events for correlated markets. Menezes (2013) has investigated the stock market co-integration effect by applying a framework of Granger Causality Test. As Granger Causality Test could capture the real relationship between the data groups, this study has taken this advantage to identify the contagion effect. Menezes (2013) selects the natural logarithm of relative stock market indices prices of the G7 group and finds strong evidence of globalization.

More recently, Croux and Reusens (2013) have tried to apply Granger Causality analysis into domestic stock prices to forecast the domestic economic events in the future, which is under the domain of frequency. There is powerful evidence that slowly fluctuating components of the stock prices could be able to forecast the future GDP for G7 group, but this fact is weak for the rapidly fluctuating components. They suggest that slowly fluctuating components of the stock prices could be help to forecast the future macro economy. Although this study focuses on the quarterly data, it is still a successful application example for Granger Causality analysis. Pimentel and Choudhry (2014) take the example of Brazil from May 1986 to May 2011 to examine the relationship between high inflation and interest rates in the stock markets. Granger Causality Test is also introduced into this study that high inflation and interest rates can be the Granger Cause for the other one, which means the significant evidence of co-interaction.

Granger Causality in risk provides a good approach to test whether empirical samples reflect contagion risk. Understanding the existence of risk spillover would contribute to better forecast and monitoring of financial markets.

3. METHODOLOGY

3.1 Data Selection

The information needed to complete this work includes the stock market indices of selected countries during the financial crisis periods. In order to distinguish the differences between the crises, two financial crises are included in this study. Current Eurozone Crisis represents the extreme downside event which transmits from developed markets to emerging markets, whereas Asian Crisis in 1997 spread from emerging markets to developed markets. For Asian financial crisis which occurred in 1998, the sample period should between 1997 Jan 1st and 1999 Dec 31st, whereas the time period is from 2009 June 1st to 2014 May 31st for current Eurozone Crisis started in 2010. Considering the lagging effect of financial crisis, the samples are selected as wide enough to cover the main period of financial crisis.

Table 1 Stock Indices

Type	Time Period	Country	Stock Indices
Developed Countries	1997.1-1999.12 2009.6-2014.5	US	Dow Jones Industrial Average
		Canada	S&P/TSX Composite Index
		France	CAC 40
		Germany	DAX
		Italy	FTSE MIB
		UK	FTSE 100
		Japan	Nikkei 225
Emerging Markets	1997.1-1999.12 2009.6-2014.5	Brazil	Ibovespa
		China	SSE Composite Index
		India	BSE SENSEX
		Russia	RTS Index
Benchmark for Eurozone Crisis	2009.6-2014.5	Spain	IBEX 35
		Portugal	PSI Geral
		Greece	FTSE/ATHEX LARGE CA (Athex 20)
		Ireland	ISEQ Overall Price
Benchmark for Asian Crisis	1997.1-1999.12	Indonesia	JSX Composite
		South Korea	KOSPI
		Thailand	SET Index

Daily stock price indices data would be selected from main developed markets (G7 group: US, UK, France, Japanese, Germany, Canada, Italy), emerging markets (BRICs countries: Brazil, China, India, Russia) and benchmark countries (Spain, Portugal, Greece and Ireland for Eurozone crisis in 2010, while Indonesia, South Korea and Thailand for Asian financial crisis in 1997), as these groups can represent the corresponding markets. The selected stock indices of different countries are listed above (Table 1). The data is obtained with daily close prices of stock indices from DataStream.

The study would mainly base on quantitative research method by analysing second hand data. The main objective of this research is to identify whether there exists a contagion risk across both emerging and developed stock markets after the shock took place and how it influences. E-GARCH (1, 1) VaR model with Generalized Error Distribution (GED) would be used to forecast the volatility results and compare the outcomes of volatility and Value-at-Risk evaluation for all the markets.

Then, it should compare the results with two groups of samples (Eurozone and Asian Crisis). The VaR evaluation of stock price indices with volatility is necessary to test the correlation. E-GARCH (1, 1) VaR model with Generalized Error Distribution (GED) would be specified to investigate market interdependence and volatility effects across the countries. To evaluate the model validation, Unconditional Coverage Test (Kupiec) as well as Conditional Coverage Test (Christoffersen) would be applied to check if the selected model and distribution could fit all the samples. At last, the correlation relationship would be tested by Granger Causality Test to find whether there exists the contagion risk between stock markets by selected model.

3.2 Returns

Simply, this study uses P_t to represent one close price of stock index at time t. Then, log return is applied to evaluate the stock index returns R_t, which holds the definition as following (Meucci, 2010).

$$R_t = ln\left(\frac{P_t}{P_{t-1}}\right) = ln(P_t) - ln(P_{t-1})$$

The return period is set from time t-1 to time t and log function here is the natural logarithm. So we can explain time series R_t as following.

$$R_t = \mathrm{E}(R_t|R_{t-1}) + \varepsilon_t$$

In this formula, the term of $\mathrm{E}(R_t|R_{t-1})$ indicates the conditional mean of R_t, while R_{t-1} is the stock index returns at time t-1; and ε_t defines as the shift of stock index close price return at time t. In addition, term σ_t is the square root of series variance with the positive value, which is referred as the following.

$$\sigma_t^2 = Var(\varepsilon_t)$$

3.3 GARCH Model

After the basic definitions, the autoregressive conditional heteroskedastic model (ARCH) should be mentioned. Engle (1982) has firstly developed the ARCH approach to generate observed time series to build forecast model when the error term would have a variance at any point in the series. The assumption of special ARCH models is that the current error term can be presented by a function of previous time periods' error terms with actual sizes, where the variance is usually correlated to the previous error terms (Engle and Bollerslev, 1986). For ARCH model, the particular asset return would have a shift ε_t, which is serially uncorrelated. Also, ε_t is dependent and can be presented with simple quadratic function with the lag values of itself. Formally, an ARCH (q) model can be shown as following.

$$\varepsilon_t = \sigma_t * z_t$$

$$\sigma_t^2 = a_0 + \sum_{i=0}^{q} a_i * \varepsilon_{t-i}^2$$

In the formula of ARCH (q), z_t is often referred as a series of random variables which follows the N (0, 1) distribution. The formula of ARCH (q) needs to satisfy the conditions that a_0 > 0 and a_i ≥ 0 (where i > 0 until q).

However, empirical studies indicate that a high value of p must be used to model the suitable conditional variance (Angelidis et al., 2004). If the lag of ARCH models is too large, ARCH model would need many parameters to describe the volatility of the return. Bollerslev (1986) has developed the ARCH theory of Engle (1982), which is known as the GARCH (p, q) model. For the theory of Bollerslev (1986), the Generalized ARCH model, known as GARCH (p, q) model, is shown as following.

$$\sigma_t^2 = a_0 + \sum_{i=0}^{q} a_i * \varepsilon_{t-i}^2 + \sum_{j=0}^{p} b_j * \sigma_{t-j}^2$$

The formula of GARCH (p, q) needs to satisfy the conditions that a_0 > 0 and a_i ≥ 0 (where i > 0 until q), while b_0 > 0 and b_j ≥ 0 (where j > 0 until p).

Compared with ARCH (q) model, the GARCH (p, q) model can capture the thick tailed returns and volatility clustering of financial time series (Angelidis et al., 2004). Drawback also plays a role in the GARCH (p, q) model that this model needs a lot of samples or observations to estimate the parameters. Additionally, GARCH (p, q) model proposes a shortcoming that odds with the empirical behaviour could produce a leverage effect in the stock market prices, as the variance hinges on magnitude and but not on the sign of ε_t. Some studies illustrate that changes in returns could be inversely correlated with the changes in the stock returns volatility (Black, 1976). In other words, volatility would climb when negative events come ($\varepsilon_t < 0$), whereas volatility would drop if there is good news ($\varepsilon_t > 0$). More recently, Brooks and Persand (2003) address that GARCH (p, q) model might miss the asymmetric information when generates the VaR values. Hence, inadequate results may lead to unreasonable predictions.

3.4 E-GARCH Model

Considering the unreasonable predictions, Nelson (1991) has proposed a new model to fit the asymmetric information in the empirical data, which is the exponential general autoregressive conditional heteroskedastic model (E-GARCH). Generally, an E-GARCH (p, q) can be presented as following.

$$\ln(\sigma_t^2) = a_0 + \sum_{\mathrm{i=0}}^{\mathrm{q}} \left(a_i \left| \frac{\varepsilon_{t-i}}{\sigma_{t-i}} \right| + \gamma_i \frac{\varepsilon_{t-i}}{\sigma_{t-i}} \right) + \sum_{\mathrm{j=0}}^{\mathrm{p}} b_j \ln(\sigma_{t-j}^2)$$

Compared with the standard GARCH (p, q) model, E-GARCH (p, q) model does not have any limitation on the estimating the parameters, due to the logarithmic form enables the prediction to be non-negative values, as the γ_i term could fit the asymmetric information (Brandt and Jones, 2006). Actually, E-GARCH (p, q) model relaxes the restriction on model coefficients by using logged conditional variance that can cover the drop or rise in the samples. Both positive and negative lagged values of positive and negative lagged values can be reflected asymmetrically in E-GARCH (p, q) model, which makes the leverage effect become significant.

3.5 Value-at-Risk

As mentioned before, Value-at-Risk (VaR), which defines as p% of loss, is a widely used measurement in risk management (Beder, 1995). The risk measure of VaR gives probabilities with specific loss amount, which is simple to understand and relatively easy to backtesting.

Given a confidence level $\alpha \in (0, 1)$, the smallest value l defines the α confidence level of VaR values, and the probability that the loss L exceeds l would be at the opposite position, which is $(1 - \alpha)$ confidence level. For this aspect, the L represents the loss of a particular asset. Thus, the VaR value defined the α confidence level could be shown as following (Artzner et al., 1999).

$$\mathrm{VaR}_{\alpha}(L) = inf\{l \in R: P(L > l) \leq 1 - \alpha\} = inf\{l \in R: F_L(l) \geq \alpha\}$$

Some studies address that VaR reflects each point of the tails estimated in empirical data (Angelidis and Degiannakis, 2007). Dowd (2005) emphasizes that VaR makes a methods to critically consider the risk exposure by an imposition on structure. Additionally, VaR measures risk factors in a consistent way. It enables that the risk is assessed as a whole of portfolio risk (Hull, 2012). In other words, it has taken account of risk interaction with each other at the firm wide level. Hence, the process of estimating VaR values should be very important to measure the exposure adequately.

3.6 Distribution

When applying parametric approach, the logic here is to estimate risk by fitting probability curves to the data and then inferring the risk measure from the fitted curve (Hull, 2012). Empirical return processes usually have the features like heavy tails, excess kurtosis and skews as well. Parametric approach therefore tests whether there exists distribution could accommodate the features.

When modelling the data statistically, the difference between the observed values and the expected values are regarded as errors. In the early studies, researchers assume the errors are random variable which is under the standard normal distribution with mean zero and standard deviation one. However, many empirical studies have identified that standard normal distribution cannot satisfy the empirical data appropriately. As a result, Generalized Error Distribution (GED) is developed to cover the requirement. Nelson (1991) has applied Generalized Error Distribution (GED) into linear regression models to analyse the time series with heavy tails. As for the definition, Generalized Error Distribution (GED) is symmetric distribution member of the exponential family. Three parameters define this distribution that μ is the location of this distribution, and σ is the standard deviation of the distribution and κ determines the skewness of this distribution. The formula of $x \sim G(\mu, \sigma^2, \kappa)$ can be shown, where x is the domain of probability density function. Thus, the probability distribution function F(x) can be presented as following (Nelson, 1991).

$$\mathrm{dF}(x|\mu,\sigma,\kappa)=\frac{e^{-\frac{1}{2}\left|\frac{x-\mu}{\sigma}\right|^{\frac{1}{\kappa}}}}{2^{\kappa+1}\sigma\Gamma(\kappa+1)}dx$$

The reason why applies the Generalized Error Distribution (GED) into this study is that Generalized Error Distribution (GED) can fit the fat and thin tails smoothly, as the samples included during the crisis periods may have strong evidence of skewness and kurtosis. Using standard Normal Distribution may lead to unreasonable results. Generalized Error Distribution (GED) allows us fit the samples with E-GARCH (1, 1) VaR model accurately.

3.7 Backtesting

When estimating VaR model, model validation should be checked to identify whether the model could produce reasonable forecasts (Dowd, 2005). Since the forecasts rely heavily on the estimates, small bias in the modelling process might cause large failure in the forecasts, so backtesting plays a critical role in the risk measurement. It could give indication of possible problems and help to track the mistakes, such as misspecification, under-estimation of tail risks and so on. Basic idea for backtesting is to compare the VaR forecasts with the associated portfolio returns (Jorion, 2009). Backtesting techniques allow us to verify the accuracy of VaR models. If the actual returns exceed the VaR forecasts, it means that the violation does occur and the VaR model should be re-estimated by changing components. In this paper, both Unconditional Coverage Test (Kupiec) and Conditional Coverage Test (Christoffersen) generate the results, and null hypotheses are the same that the exceedances are correct, while the alternative ones are the model is not appropriate.

When taking backtesting, it needs to count the VaR violations first. VaR violation refers to the number of time series exceeding the forecast VaR values. If the VaR model is good, the violation number should equal or under the excepted number, or in other words, falls in the range of permitting expected exceeding values. Thus, the formula of violation number can be shown as following.

$$I_{t+1} = \begin{cases} 0, if\ R_{t+1} \geq VaR_{t+1} \\ 1, if\ R_{t+1} < VaR_{t+1} \end{cases}$$

Definitely, the violation number (N) is the total number of series I_{t+1}, which generates the total failure forecasts of VaR values. The most common way of backtesting is to count the violations of VaR values but this method proposes the problem that whether we observe the exact number of violations. Backtesting in the early time is a basic frequency test that checks whether the forecast exceptions of VaR frequency have coherent results with the general frequency of exceptions under the particular confidence level. The null hypothesis is the model exceeds are correct, while the alternative ones are the model is not appropriate. The number of tail losses x is binomial, while the n is the number of observations and $(1 - p)$ is the selected confidence interval. So the probability of Bernoulli sequence is as following (Jorion, 2009).

$$\Pr(x = k|n, p) = \binom{n}{k} p^k (1 - p)^{n-k}$$

If the estimated probability is above the desired level (95% confidence level, so 5% for desired value), the VaR model cannot reject the null hypothesis of correct exceeds. Then, the model is good. If the estimated probability is below the desired level, there could be some problems in the model. The basic frequency test is easy to implement that it does not require too much information, but it is still under criticism as the basic frequency test throws information away and might be not reasonable with small sample sizes. More exactly, the basic frequency test only reflects the frequency of exceptions but has not given any idea on the time dynamics of the exceptions (Dowd, 2005). For example, the accuracy of this formula is doubtable that there is a trade-off between Type 1 error (the possibility of rejecting a correct model) and Type 2 error (the possibility of accepting a wrong model). Jorion (2009) suggests that these two types of error should minimize in the statistical test.

Therefore, Kupiec (1995) has developed Unconditional Coverage Test (Kupiec) for backtest the values of VaR. For Unconditional Coverage Test (Kupiec), the null hypothesis is that failure rate f would be equal to the excepted level p, where x is the number of tail losses, n is the number of observations and $(1-p)$ is the selected confidence interval.

$$f = \frac{x}{n} = p$$

That whether the exceeds are correct can be examined by using the likelihood ratio as following, where x is the number of tail losses that follows the binomial distribution, n is the number of observations and $(1-p)$ is the selected confidence interval (Jorion, 2009).

$$LR_{UC} = -2ln[(1-p)^{n-x}p^x] + 2ln\left[\left(\frac{1-x}{n}\right)^{n-x}\left(\frac{x}{n}\right)^x\right]$$

If the estimated likelihood is below the critical value (95% confidence level, so 5% for desired value), the VaR model cannot reject the null hypothesis of correct exceeds. Then, the model is good. However, if the estimated likelihood is larger than the corresponding critical value, there could be some problems in the model. However, the Unconditional Coverage Test (Kupiec) has the shortcoming that the same samples may have different variances for sub-series (Dowd, 2005). As a result, the VaR model ignores important information that leads to inconsistent results. Nonetheless, it is still a good approach for backtesting.

In order to avoid the bias, Conditional Coverage Test (Christoffersen) is introduced into this study as well. Christoffersen (1998) proposed another statistic specifying that the deviations must be serially independent. Conditional Coverage Test (Christoffersen) captures both the frequency and independence of exceptions (Jorion, 2009), where the null hypothesis of this test is that the exceeding is correct and independent. The formula of Conditional Coverage Test (Christoffersen) is shown as following, where x is the number of tail losses that follows the binomial distribution, the n is the number of observations and p is the selected confidence interval (Christoffersen and Pelletier, 2004). The standard deviation indicates the range between 0 (no violation occurs) and 1 (violation occurs). Then, T_{ij} is the number of days when condition j occurred with the assumption that condition i occurred on the previous day. In addition, π_i refers to the probability of detecting an exception condition i at the previous day. Thus, the formula is as following (Christoffersen, 2009).

$$LR_{ind} = -2ln[(1-\pi)^{T_{00}+T_{10}} * \pi^{T_{01}+T_{11}}] + 2ln[(1-\pi_0)^{T_{00}} * \pi_0{}^{T_{01}} * (1-\pi_1)^{T_{10}} * \pi_1{}^{T_{11}}]$$

The second half part indicates the maximized likelihood for the observed data, while the first half part of this formula is the maximized likelihood, where the null hypothesis is that violations are independent with the days as following.

$$\pi = \pi_0 = \pi_1 = \frac{T_{01} + T_{11}}{T}$$

Thus, the statistic for Conditional Coverage Test (Christoffersen) is shown as following (Christoffersen, 2009).

$$LR_{CC} = LR_{UC} + LR_{ind}$$

If the estimated statistic is below the critical value at selected confidence interval (95% confidence level), the VaR model cannot reject the null hypothesis of correct exceeds and independence. Thus, the model can pass Conditional Coverage Test (Christoffersen). However, if the estimated statistic is above the critical value, there could be some problems in the model.

Conditional Coverage Test (Christoffersen) can identify the model with too many clustered violations and capture the feature of current risk. In general, it would be reasonable to base on both Unconditional Coverage Test (Kupiec) and Conditional Coverage Test (Christoffersen) to analyse the problem.

3.8 Granger Causality Test

Perhaps, how to detect the contagion risk within the financial crises is the most important topic in this study. Granger Causality Test in risk is applied into this paper to evaluate the extreme downside events among the stock markets.

As for the definition, Granger Causality Test is referred as a statistical hypothesis test to examine whether the selected time series can be the reason to influence another time series

(Engle and Granger, 1987). Granger (2004) emphasizes that applying the historical data of one time series could contribute to forecast the parameters of another time series in the future. When this relationship is significant, the former time series can be viewed as the Granger Cause of the latter time series. Although the E-GARCH (1, 1) model with Generalized Error Distribution (GED) could estimate parameters and give prediction on VaR values, it still lacks the ability to judge the relationship or contagion effect between different financial markets. Considering the original concept of Granger Causality Test, it is an excellent approach to examine the risk spillover in the financial crisis. The theoretical idea in this study is to compare one stock index with another one to check whether the market forecast can be influenced by another one (Granger, 1988). If this kind of mechanism is significant at the selected confidence interval, the latter time series can be concluded as the Granger Cause for the former one. In other words, one market probably will suffer the risk spillover when the correlated markets have extreme negative events. This application could make contribution to effective financial risk management, as well as investment diversification.

If y_t and x_t are two stationary time series, the null hypothesis that x_t is not the Granger Cause of y_t with appropriate lag value m can be tested as following.

$$y_t = a_0 + a_1 y_{t-1} + a_2 y_{t-2} + \cdots + a_m y_{t-m} + \varepsilon_t$$

$$y_t = a_0 + a_1 y_{t-1} + a_2 y_{t-2} + \cdots + a_m y_{t-m} + b_p y_{t-p} + \cdots + b_q y_{t-q} + \varepsilon_t$$

Above presentation includes the shortest p and longest q lag values for the variable x_t, while ε_t is the residuals of the formula. If the variable x stays in the regression of the univariate auto-regression of variable y_t, the null hypothesis would not be rejected and variable x_t can be concluded as the Granger Cause of variable y_t (Hiemstra and Jones, 1994).

The assumption here is that the all the testing time series should be stationary, while non-stationary could be used by applying the first (or higher) differences. Note that the Granger Cause Test has a lagged value to estimate the results, which would indicate different conclusion with inconsistent lag values (Granger, 1969). Information criterion, such as

Akaike Information Criterion (AIC) and Schwarz Information Criterion (BIC), is responsible to select the best lag value (Granger, 2004). Many empirical studies may have the results that neither time series can be the Granger Cause for the other one, while another condition is that each time series can be the Granger Cause for the other. It is not limited by one condition.

4. DATA AND RESULTS

4.1 Eurozone Crisis

4.1.1 Date Requirement (Eurozone Crisis)

In order to explore the contagion risk between different financial markets, it is important to estimate E-GARCH model for each sample first, after which could evaluate the risk spillover. According to different developing levels of financial markets, three types of stock indices are presented, what are developed markets (G7 groups: US Dow Jones Industrial Average, Canada S&P/TSX Composite Index, France CAC 40, Germany DAX, Italy FTSE MIB, UK FTSE 100 and Japan Nikkei 225); emerging markets (the four countries of BRICs: Brazil Ibovespa, India BSE SENSEX, China SSE Composite Index and Russia RTS Index); and benchmark markets (the countries suffer the most loss in the Eurozone Crisis: Spain IBEX 35, Portugal PSI Geral, Greece FTSE/ATHEX LARGE CA and Ireland ISEQ Overall Price). The daily stock close prices are used to perform log returns. And the period concerned is from June 1st 2009 to May 31st 2014 obtained from DataStream that covers the Eurozone Crisis.

All the plotting of stock indices in the Eurozone Crisis are shown in the Appendix (from Figure 1 to Figure 15), while the plotting of returns are shown in the Appendix as well (from Figure 16 to Figure 30).

4.1.2 Data Description (Eurozone Crisis)

To begin with, whether the samples are stationary should be checked by Augmented Dickey-Fuller test (ADF). If the selected stock indices can satisfy the assumptions, they can have further analysis. The null hypothesis: the series is non-stationary, while the alternative hypothesis: the series is stationary. The significant level applied here is 95% level.

Table 2 Augmented Dickey-Fuller test (Eurozone Crisis)

Test / Sample	Unit Root (ADF test)			
	Statistics	p-value	Critical Values	
United Kingdom	-19.24920	0.00000	1% level	-3.43000
United States	-17.69890	0.00000	5% level	-2.86000
Canada	-14.06840	0.00000	10% level	-2.57000
France	-19.76270	0.00000		
Germany	-21.66660	0.00000		
Italy	-19.49160	0.00000		
Japan	-18.55760	0.00000		
Brazil	-24.72360	0.00000		
China	-24.54500	0.00000		
India	-20.48300	0.00000		
Russia	-23.68740	0.00000		
Spain	-20.32320	0.00000		
Portugal	-19.61950	0.00000		
Greece	-26.46120	0.00000		
Ireland	-27.07910	0.00000		

In the Table 2, it is clear that all the stock indices reject the null hypothesis of non-stationary at any significant level. Thus, the samples with log returns form can be used to further study.

As we can see, Table 3 shows the basic features of daily log returns of the 15 indices during Eurozone Crisis. It is obvious that each stock index holds strong skewness and kurtosis, which means that most indices appear to have fat tails and left skewness. From the descriptive statistics, it indicates that Normal Distribution might not be suitable for estimating E-GARCH model.

In addition, Table 4 presents the Jarque-Bera (JB) test and Ljung-Box Q-statistic for selected stock indices. At any significant level of Jarque-Bera (JB) test, the null hypothesis of Normal Distribution is rejected in all cases, which proves the inference of strong skewness and kurtosis. Note that the Ljung-Box Q-statistic, which is tested for the squared series with order 7, reflects a high serial correlation in the variance. The reason to choose order 7 is that, Tsay (2005) suggests that simulation studies could apply the degrees of freedom as ln(M), where M is the number of observations. This would perform better in the simulations.

Table 3 Description of Samples (Eurozone Crisis)

Statistic / Sample	Description			
	Mean	Std. Deviation	Skewness	Kurtosis
United Kingdom	0.00032	0.01010	-0.19234	2.08341
United States	0.00057	0.01048	-0.47977	3.97230
Canada	0.00025	0.00884	-0.43961	2.34335
France	0.00023	0.01376	-0.01113	3.21198
Germany	0.00051	0.01297	-0.21097	2.29189
Italy	0.00004	0.01656	-0.08885	2.45791
Japan	0.00034	0.01403	-0.73086	4.53779
Brazil	-0.00005	0.01388	-0.19664	1.82796
China	-0.00023	0.01281	-0.46905	2.57747
India	0.00040	0.01142	-0.07856	1.24071
Russia	0.00008	0.01805	-0.50676	3.59872
Spain	0.00009	0.01581	0.30096	5.24294
Portugal	0.00014	0.01176	0.14593	5.74335
Greece	-0.00089	0.02541	0.28447	2.52730
Ireland	0.00043	0.01287	-0.29746	2.60791

Table 4 Description of Samples (Eurozone Crisis)

Statistic / Sample	Description			
	JB Statistics	JB p-value	LB Q(7)	LB p-value
United Kingdom	244.92110	0.00000	244.93490	0.00000
United States	880.09440	0.00000	463.19450	0.00000
Canada	334.98200	0.00000	263.72630	0.00000
France	554.45180	0.00000	179.55300	0.00000
Germany	291.91740	0.00000	351.43420	0.00000
Italy	324.86800	0.00000	169.05020	0.00000
Japan	1172.69500	0.00000	140.57800	0.00000
Brazil	181.98100	0.00000	114.55720	0.00000
China	391.84810	0.00000	88.13410	0.00000
India	81.56210	0.00000	131.22970	0.00000
Russia	734.44570	0.00000	64.66660	0.00000
Spain	1490.31500	0.00000	169.38010	0.00000
Portugal	1740.50300	0.00000	127.05880	0.00000
Greece	367.00280	0.00000	118.73010	0.00000
Ireland	384.09600	0.00000	207.06310	0.00000

4.1.3 Estimation of E-GARCH VaR Models (Eurozone Crisis)

After describing the main features of selected stock indices, especially the volatility clustering, E-GARCH (1, 1) Model is adopted to fit in all cases. During the estimating process, a confidence level of 95% is adopted for all the p-values. In Table 4 and Table 5, parameter values for estimating E-GARCH models have shown in the first row of each stock index, while the second row presents the p-values for different parameters.

According to the strong skewness and kurtosis, Generalized Error Distribution (GED) generates the parameters. Concretely, a confidence of 95% is adopted to evaluate the performance of assumption. As the results in Table 5 and Table 6, the model of E-GARCH (1, 1) under the Generalized Error Distribution (GED) is valid for most series. However, several indices have not passed the 95% confidence level with some parameters, such like Italy, China, Brazil and India, which might produce unstandardized residuals. This brings doubts on the assumptions of choosing distribution and model. We will discuss it in Backtesting Section later.

Table 5 E-GARCH Model Parameters 1-2 (Eurozone Crisis)

Estimate / Sample	E-GARCH Model Parameters			
	Mean	AR Term	MA Term	Constant
United Kingdom	0.00035	0.97254	-0.97853	-0.41067
	0.02110	0.00000	0.00000	0.00000
United States	0.00065	-0.71156	0.69078	-0.44948
	0.00024	0.00000	0.00000	0.00000
Canada	0.00033	-0.15949	0.20204	-0.19871
	0.04210	0.00106	0.00003	0.00000
France	0.00022	-0.16282	0.13109	-0.33900
	0.33513	0.00032	0.00462	0.00000
Germany	0.00062	-0.97585	0.99038	-0.26940
	0.01330	0.00000	0.00000	0.00000
Italy	0.00026	-0.26484	0.25936	-0.25666
	0.49598	0.02887	0.03255	0.00000
Japan	0.00046	-0.29217	0.24934	-0.74400
	0.02611	0.00000	0.00000	0.52312
Brazil	-0.00031	0.90707	-0.89914	-0.40055
	0.46073	0.00000	0.00000	0.00000
China	0.00002	0.08415	-0.09065	-0.15353
	0.97407	0.02534	0.00000	0.00000
India	0.00020	0.27342	-0.21378	-0.27276
	0.49492	0.00000	0.00000	0.00000
Russia	0.00029	0.10165	-0.03852	-0.14324
	0.50180	0.08501	0.50512	0.00000
Spain	-0.00004	-0.00110	0.06201	-0.20395
	0.90416	0.99128	0.53423	0.00000
Portugal	0.00034	0.08463	-0.01515	-0.46632
	0.08850	0.17578	0.83812	0.00000
Greece	-0.00052	-0.71518	0.75902	-0.23954
	0.04055	0.00000	0.00000	0.00200
Ireland	0.00063	0.75994	-0.80658	-0.25407
	0.00737	0.00000	0.00000	0.00000

Table 6 E-GARCH Model Parameters 2-2 (Eurozone Crisis)

Estimate / Sample	E-GARCH Model Parameters				
	ARCH Term	GARCH Term	Asymmetry Term	Shape	Log-Likelihood
United Kingdom	-0.14519	0.95657	0.15197	1.44263	4279.57200
	0.00000	0.00000	0.00000	0.00000	
United States	-0.21629	0.95306	0.13774	1.33271	4166.82500
	0.00000	0.00000	0.00000	0.00000	
Canada	-0.14198	0.98008	0.09745	1.48372	4395.77900
	0.00000	0.00000	0.00000	0.00000	
France	-0.20367	0.96208	0.10536	1.46933	3850.72500
	0.00000	0.00000	0.00000	0.00000	
Germany	-0.15915	0.97039	0.12078	1.37980	3932.69300
	0.00000	0.00000	0.00000	0.00000	
Italy	-0.12410	0.96979	0.09038	1.58288	3548.24600
	0.00000	0.00000	0.00000	0.00000	
Japan	-0.10048	0.91408	0.17906	1.53389	3586.68600
	0.22256	0.00000	0.00000	0.00000	
Brazil	-0.10417	0.95363	0.10513	1.67074	3600.76800
	0.00000	0.00000	0.00003	0.00000	
China	-0.01147	0.98258	0.07677	1.09903	3740.72000
	0.39464	0.00000	0.00000	0.00000	
India	-0.11232	0.96999	0.10825	1.55463	3871.49400
	0.00000	0.00000	0.00000	0.00000	
Russia	-0.06894	0.98276	0.09769	1.29256	3394.57300
	0.00000	0.00000	0.00000	0.00000	
Spain	-0.13783	0.97627	0.09601	1.58501	3642.99400
	0.00000	0.00000	0.00000	0.00000	
Portugal	-0.11082	0.94888	0.12872	1.56283	3927.38700
	0.00000	0.00000	0.00000	0.00000	
Greece	-0.03432	0.96781	0.13217	1.28567	3030.33200
	0.04597	0.00000	0.07400	0.00000	
Ireland	-0.05185	0.97159	0.16963	1.57821	3882.36300
	0.00305	0.00000	0.00000	0.00000	

After focus on the parameters, it is essential to check whether the model has collected all the necessary information. The E-GARCH model generates Ljung-Box Q-statistics for both Standardized Residuals and Standardized Squared Residuals with 1, 5 and 9 lags. As the Table 7 shows, all Standardized Residuals of the stock indices cannot reject the null hypothesis of randomness at a significant level of 95%, except for Ireland ISEQ Overall Price stock index. In other words, most Standardized Residuals of the stock indices have independent distribution, where there is no autocorrelations from the samples. Thus, any observed correlations could be resulted from randomness of the sampling process (Ljung and Box, 1978). Although Ireland ISEQ Overall Price stock index is the only one to reject the null hypothesis and shows distributed dependently, E-GARCH (1, 1) model with Generalized Error Distribution (GED) can fit most samples. This proves that the choice of model is appropriate. Table 8 also testifies this inference that the almost all the Standardized Squared Residuals of selected indices after modelling cannot reject the null hypothesis of independent distribution with 1, 5 and 9 lags, while only United States Dow Jones Industrial Average reveals autocorrelation from the sample. Finally, Weighted ARCH Lagrange Multiplier Test (Table 9) provides the evidence as well that only Italian stock index FTSE MIB with 3 lags and Spain IBEX 35 with 5 and 7 lags reject the null hypothesis of no ARCH effect, while all the others cannot reject the null hypothesis. It means that there is no ARCH effect in the residuals after modelling. More specifically, the residuals left are white noise, which means all valuable information has been collected. Nonetheless, considering all these evidences given by these tests, E-GARCH (1, 1) model with Generalized Error Distribution (GED) can fit selected stock indices accurately and give reasonable forecasts.

Table 7 E-GARCH Model Tests 1-3 (Eurozone Crisis)

Test / Sample	E-GARCH Model Tests		
	LB Test on Standardized Residuals		
	lag=1	lag=5	lag=9
United Kingdom	0.12470	0.72850	1.85850
	0.72400	1.00000	0.98970
United States	0.18650	2.71900	4.38410
	0.66580	0.65100	0.59920
Canada	0.01514	3.56428	6.27691
	0.90210	0.18110	0.21400
France	0.06210	2.98820	4.51390
	0.80320	0.47940	0.56790
Germany	0.00442	2.43582	3.53839
	0.94700	0.81150	0.79340
Italy	0.01639	0.83072	1.46840
	0.89810	1.00000	0.99740
Japan	0.34790	1.70750	2.66750
	0.55530	0.99110	0.93450
Brazil	0.00034	0.36963	1.49743
	0.98530	1.00000	0.99710
China	0.20990	1.53370	4.49670
	0.64690	0.99740	0.57210
India	0.00017	0.58941	1.39625
	0.98960	1.00000	0.99810
Russia	0.04684	0.93448	2.75523
	0.82870	1.00000	0.92420
Spain	0.07485	2.01268	3.41949
	0.78440	0.95570	0.81740
Portugal	0.23890	1.57830	3.23290
	0.62500	0.99630	0.85220
Greece	0.59390	1.12600	1.55210
	0.44090	1.00000	0.99640
Ireland	5.36700	7.50600	8.76900
	0.02053	0.00000	0.02947

Table 8 E-GARCH Model Tests 2-3 (Eurozone Crisis)

Test / Sample	E-GARCH Model Tests		
	LB Test on Standardized Squared Residuals		
	lag=1	lag=5	lag=9
United Kingdom	4.63100	5.10000	5.48200
	0.03140	0.14530	0.36220
United States	10.33000	12.41000	15.99000
	0.00131	0.00217	0.00205
Canada	8.13700	10.55300	13.97600
	0.00434	0.00664	0.00630
France	1.82800	2.64900	3.13700
	0.17630	0.47500	0.73620
Germany	3.60200	4.03600	4.31900
	0.05770	0.24960	0.53570
Italy	1.70600	5.57000	7.02400
	0.19150	0.11330	0.19720
Japan	0.58200	1.42100	3.36000
	0.44550	0.75940	0.69840
Brazil	0.29320	2.40030	3.07500
	0.58820	0.52730	0.74650
China	1.09300	3.41100	6.86000
	0.29570	0.33700	0.21120
India	0.19680	1.66890	2.88790
	0.65740	0.69840	0.77730
Russia	0.18080	0.54930	1.48830
	0.67060	0.94980	0.95650
Spain	1.77400	6.61600	9.84100
	0.18294	0.06421	0.05424
Portugal	5.38600	5.54800	6.07900
	0.02030	0.11470	0.28920
Greece	0.17700	2.55600	5.04200
	0.67390	0.49410	0.42320
Ireland	0.94740	6.43980	8.94160
	0.33039	0.07075	0.08356

Table 9 E-GARCH Model Tests 3-3 (Eurozone Crisis)

Test / Sample	E-GARCH Model Tests		
	Weighted ARCH LM Tests		
	lag=1	lag=5	lag=9
United Kingdom	0.01710	0.09792	0.13667
	0.89600	0.98720	0.99870
United States	0.70440	1.62550	5.34750
	0.40130	0.56000	0.19170
Canada	1.30900	4.57500	6.69400
	0.25260	0.12870	0.10100
France	0.37790	0.69650	0.93190
	0.53870	0.82450	0.92440
Germany	0.41360	0.62520	0.78760
	0.52020	0.84610	0.94550
Italy	4.72100	5.26600	5.66100
	0.02980	0.08915	0.16570
Japan	0.00048	2.06180	2.62167
	0.98250	0.45770	0.58760
Brazil	0.16560	0.18270	0.61110
	0.68400	0.96950	0.96730
China	0.29680	2.18990	5.41550
	0.58590	0.43080	0.18580
India	0.88970	1.92400	2.61320
	0.34560	0.48830	0.58940
Russia	0.03844	0.67894	0.79281
	0.84460	0.82990	0.94480
Spain	0.00860	7.97888	8.70460
	0.92613	0.02031	0.03648
Portugal	0.12130	0.14220	0.76650
	0.72760	0.97850	0.94830
Greece	2.79200	3.62900	5.73000
	0.09475	0.21068	0.16046
Ireland	0.09516	0.71850	2.62337
	0.75770	0.81780	0.58730

4.1.4 Backtesting (Eurozone Crisis)

As a critical part of risk measurement, backtesting gives indication of possible problems on the model validation. It relies heavily on the estimates. To avoid the mistakes, both Unconditional Coverage Test (Kupiec) and Conditional Coverage Test (Christoffersen) generate the results, and null hypotheses are the same that the exceedances are correct, while the alternative ones are the model is not suitable. The 95% significance level VaR values are estimate under the previous E-GARCH (1, 1) model with Generalized Error Distribution (GED). Then, estimated VaR values would compare with actual stock indices to track the violations. At last, Unconditional Coverage Test (Kupiec) and Conditional Coverage Test (Christoffersen) would put the model validation into evaluation. Note that the confidence level of both tests is at 95% level.

Based on the Table 10, actual exceedances are closed to expected exceedances. Though actual exceedances of some stock indices are more than expected exceedances, backtesting can gives indication on whether the exceedances are accepted.

Table 10 E-GARCH Model Exceedances (Eurozone Crisis)

Test / Sample	Backtesting	
	Expected Exceedances	Actual Exceedances
United Kingdom	65	75
United States	62	77
Canada	63	86
France	64	77
Germany	64	77
Italy	63	73
Japan	61	59
Brazil	61	62
China	62	58
India	61	56
Russia	62	73
Spain	63	69
Portugal	62	82
Greece	65	57
Ireland	64	73

Table 11 reports the test statistics at 95% confidence levels, together with their p-values. In the Table 11, most samples cannot reject the null hypothesis of correct exeedances, while Canada S&P/TSX composite index reject the null hypothesis for both tests (p-values are

0.00651 for Kupiec and 0.00087 for Christoffersen), and Portugal PSI Geral index reject the null hypothesis for unconditional coverage Test (p-value is 0.01768 for Kupiec). Last but not the least, E-GARCH (1, 1) model with Generalized Error Distribution (GED) is valid for the majority of selected stock indices to give adequate volatility forecasting for VaR values.

Table 11 E-GARCH Model Backtesting (Eurozone Crisis)

Test / Sample	Backtesting			
	Unconditional Coverage Tests		Conditional Coverage Tests	
	Likelihood Ratio statistic	p-value	Likelihood Ratio statistic	p-value
United Kingdom	1.54632	0.21368	2.20237	0.33248
United States	3.11494	0.07758	3.91699	0.14107
Canada	7.40428	0.00651	14.08299	0.00087
France	2.57473	0.10858	3.00008	0.22312
Germany	2.59607	0.10713	4.69605	0.09556
Italy	1.35240	0.24486	1.36151	0.50623
Japan	0.11709	0.73221	0.59757	0.74172
Brazil	0.00004	0.99480	0.49288	0.78158
China	0.29109	0.58953	0.51490	0.77302
India	0.61068	0.43453	1.90991	0.38483
Russia	1.69562	0.19286	1.83655	0.39921
Spain	0.41808	0.51790	0.58728	0.74554
Portugal	5.62756	0.01768	5.71398	0.05744
Greece	1.13162	0.28743	1.98547	0.37056
Ireland	1.27693	0.25847	2.08760	0.35211

Note: Unconditional Coverage Test Null Hypothesis (Kupiec): Correct Exceedances; Conditional Coverage Test (Christoffersen) Null Hypothesis: Correct Exceedances & Independent.

4.1.5 Granger Causality Test (Eurozone Crisis)

That being the case, the E-GARCH (1, 1) VaR model with Generalized Error Distribution (GED) is valid for selected stock indices. It is possible to verify the spillover effects among the selected stock markets. Since Spain, Portugal, Greece and Ireland suffer the largest effects in the Eurozone Crisis, Spain IBEX 35, Portugal PSI Geral, Greece FTSE/ATHEX LARGE CA (Athex 20) and Ireland ISEQ Overall Price stock indices are used in turns to find whether the selected stock indices have risk spillover effects. Additionally, Granger Causality Test in this part is estimated at a confidence level of 95%, while the lag value in each test is selected with minimum Akaike Information Criterion (AIC) value.

4.1.5.1 Granger Causality Test for Spain IBEX 35

Table 12 indicates the Granger Causality Test statistics for Spain IBEX 35 at a 95% significant level, along with the p-values, where the null hypothesis here is former index does not Granger cause the latter one (United Kingdom=>Spain means that United Kingdom FTSE 100 does not Granger cause Spain IBEX 35).

There is extreme contagion effect of five cases, where Spain IBEX 35 is the Granger cause for India BSE SENSEX, Russia RTS Index, Portugal PSI Geral and Greece FTSE/ATHEX LARGE CA (Athex 20). Then, United States Dow Jones Industrial Average and Spain IBEX 35, each of the two series Granger causes the other. The same condition appears in Italy FTSE MIB, Japan Nikkei 225, Brazil Ibovespa, China SSE Composite Index. That means that when negative shocks arises and Spain IBEX 35 has decreases sharply in the returns, the past daily return information of Spain IBEX 35 could conduce to the predict the risk in the other indices (United States Dow Jones Industrial Average, Italy FTSE MIB, Japan Nikkei 225, Brazil Ibovespa, China SSE Composite Index). It is interesting that France CAC 40 is the Granger Cause of Spain IBEX 35 (p-value is 0.02). Despite France is not the country which suffers the most serious problem in the Eurozone Crisis, it is a proof of regional contagion effect as well. On the other hand, there is no significant risk transmission between other stock indices groups, since the p-values are over 0.05 and cannot reject the null hypothesis.

Table 12 Granger Causality Test for Spain (Eurozone Crisis)

Cause / Samples	Spain		
	Statistics	p-value	Lag
United Kingdom=>Spain	1.12310	0.34370	4
Spain=>United Kingdom	0.54310	0.70410	
United States=>Spain	2.26140	0.02706	7
Spain=>United States	2.72950	0.00803	
Canada=>Spain	1.23970	0.27710	7
Spain=>Canada	1.58660	0.13460	
France=>Spain	2.92260	0.02000	4
Spain=>France	2.04590	0.08542	
Germany=>Spain	1.34790	0.24980	4
Spain=>Germany	0.11550	0.97710	
Italy=>Spain	2.47390	0.04250	4
Spain=>Italy	2.51330	0.03980	
Japan=>Spain	4.38830	0.03629	1
Spain=>Japan	196.59810	0.00000	
Brazil=>Spain	9.62380	0.00194	1
Spain=>Brazil	4.48650	0.03426	
China=>Spain	6.04900	0.01398	1
Spain=>China	19.30660	0.00001	
India=>Spain	1.65380	0.19150	2
Spain=>India	9.77490	0.00006	
Russia=>Spain	0.34050	0.55960	1
Spain=>Russia	5.68060	0.01723	
Portugal=>Spain	1.45590	0.21310	4
Spain=>Portugal	2.43600	0.04525	
Greece=>Spain	2.16970	0.06998	4
Spain=>Greece	4.02500	0.00295	
Ireland=>Spain	1.49410	0.20130	4
Spain=>Ireland	1.03050	0.39000	

4.1.5.2 Granger Causality Test for Portugal PSI Geral

Similar to the results of Spain IBEX 35, Table 13 presents the Granger Causality Test statistics for Portugal PSI Geral at a 95% significant level, along with the p-values. It is found that the presence of extreme downside shifts in the Portugal PSI Geral contributes to predict negative events in Canada S&P/TSX Composite Index, India BSE SENSEX, Russia RTS Index and Ireland ISEQ Overall Price stock indices, since Portugal PSI Geral is rejected the null hypothesis for these four series. Moreover, Brazil Ibovespa and China SSE Composite Index can Granger cause Portugal PSI Geral, while Portugal PSI Geral can Granger cause each of them as well. Two sides have a bidirectional relationship in the stock indices.

Table 13 Granger Causality Test for Portugal (Eurozone Crisis)

Samples \ Cause	Portugal		
	Statistics	p-value	Lag
United Kingdom=>Portugal	0.39100	0.53180	1
Portugal=>United Kingdom	1.63660	0.20090	
United States=>Portugal	6.14400	0.00006	4
Portugal=>United States	1.70300	0.14650	
Canada=>Portugal	1.56020	0.12160	9
Portugal=>Canada	2.15310	0.02254	
France=>Portugal	0.02290	0.87980	1
Portugal=>France	2.09060	0.14830	
Germany=>Portugal	0.09440	0.75870	1
Portugal=>Germany	0.05360	0.81700	
Italy=>Portugal	2.49590	0.11430	1
Portugal=>Italy	2.08160	0.14920	
Japan=>Portugal	7.21410	0.00728	1
Portugal=>Japan	100.00090	0.00000	
Brazil=>Portugal	29.95650	0.00000	1
Portugal=>Brazil	6.89290	0.00871	
China=>Portugal	6.23180	0.01261	1
Portugal=>China	18.86620	0.00001	
India=>Portugal	1.51490	0.21850	1
Portugal=>India	8.25300	0.00410	
Russia=>Portugal	0.79820	0.37170	1
Portugal=>Russia	8.39530	0.00380	
Spain=>Portugal	2.43600	0.04525	4
Portugal=>Spain	1.45590	0.21310	
Greece=>Portugal	5.91800	0.00010	4
Portugal=>Greece	1.40410	0.23000	
Ireland=>Portugal	0.63480	0.42570	1
Portugal=>Ireland	4.71090	0.03007	

Finally, United States Dow Jones Industrial Average, Spain IBEX and Greece FTSE/ATHEX LARGE CA (Athex 20) reject the null hypothesis, which indicates they are the Granger causes for the volatility of Portugal PSI Geral. Therefore, when the stock markets of United

States, Spain and Greece suffer extreme downside drops, Portugal PSI Geral index would have the contagion risk possibly.

4.1.5.3 Granger Causality Test for Greece FTSE/ATHEX LARGE CA (Athex 20)

The Greek government debt crisis has made a threat to European and even global financial markets since the crisis began in 2010. Thus, the Greek data is meaningful for studying the risk spillover. In the Table 14, Granger Causality Test statistics for Greece FTSE/ATHEX LARGE CA (Athex 20) are shown with p-values. As mentioned before, the confidence level stays as 95% level for all the tests.

In one aspect, declines in Greece FTSE/ATHEX LARGE CA (Athex 20) can help to forecast the negative shocks for Japan Nikkei 225, China SSE Composite Index, India BSE SENSEX and Portugal PSI Geral Greece FTSE/ATHEX LARGE CA (Athex 20), because Greece FTSE/ATHEX LARGE CA (Athex 20) is the Granger cause of these stock indices. In the other aspect, United Kingdom FTSE 100, United States Dow Jones Industrial Average, Canada S&P/TSX Composite Index, Germany DAX, Italy FTSE MIB, France CAC 40, Brazil Ibovespa and Spain IBEX 35 reject the null hypothesis, which means they are the Granger causes for extreme downside shifts in the Greece FTSE/ATHEX LARGE CA (Athex 20). There is no stock index in the samples that interact with Greece FTSE/ATHEX LARGE CA (Athex 20) or being Granger cause for each other. The majority of the selected stock indices show significant contagion effects, whereas Russia RTS Index and Ireland ISEQ Overall Price reflect no significant risk transmission with Greece FTSE/ATHEX LARGE CA (Athex 20), since the p-values are over 0.05 and cannot reject the null hypothesis for two sides.

Table 14 Granger Causality Test for Greece (Eurozone Crisis)

Samples \ Cause	Greece		
	Statistics	p-value	Lag
United Kingdom=>Greece	5.19160	0.00562	2
Greece=>United Kingdom	2.34690	0.09587	
United States=>Greece	11.03990	0.00000	3
Greece=>United States	0.70540	0.54880	
Canada=>Greece	6.93730	0.00012	3
Greece=>Canada	0.91600	0.43230	
France=>Greece	3.46850	0.03131	2
Greece=>France	1.76350	0.17160	
Germany=>Greece	5.65360	0.01749	1
Greece=>Germany	1.36390	0.24300	
Italy=>Greece	7.88070	0.00039	2
Greece=>Italy	2.99650	0.05014	
Japan=>Greece	0.46030	0.63120	2
Greece=>Japan	14.34200	0.00000	
Brazil=>Greece	22.30730	0.00000	1
Greece=>Brazil	3.83320	0.05036	
China=>Greece	0.28330	0.75330	2
Greece=>China	3.68050	0.02535	
India=>Greece	0.38640	0.53430	1
Greece=>India	5.86820	0.01549	
Russia=>Greece	2.87030	0.05687	2
Greece=>Russia	0.52890	0.58930	
Spain=>Greece	4.02500	0.00295	4
Greece=>Spain	2.16970	0.06998	
Portugal=>Greece	1.40410	0.23000	4
Greece=>Portugal	5.91800	0.00010	
Ireland=>Greece	1.30130	0.27240	2
Greece=>Ireland	2.18750	0.11240	

4.1.5.4 Granger Causality Test for Ireland ISEQ Overall Price

The last benchmark stock index for Eurozone Crisis is the Ireland ISEQ Overall Price. As shown in the Table 15, Granger Causality Test statistics for Ireland ISEQ Overall Price is the Granger cause for Japan Nikkei 225, China SSE Composite Index and India BSE SENSEX at a 95% significant level. It indicates that Ireland ISEQ Overall Price contributes to predict the extreme negative events for Japan Nikkei 225, China SSE Composite Index and

India BSE SENSEX. Also, United Kingdom FTSE 100, United States Dow Jones Industrial Average, Canada S&P/TSX Composite Index, Germany DAX, Italy FTSE MIB, Brazil Ibovespa and Portugal PSI Geral reject the null hypothesis that they are the Granger cause for Ireland ISEQ Overall Price. However, others have not presented any significant evidence. Notably, there is no series could interact with testing stock indices (Greece and Ireland).

Table 15 Granger Causality Test for Ireland (Eurozone Crisis)

Cause / Samples	Ireland		
	Statistics	p-value	Lag
United Kingdom=>Ireland	3.08040	0.04611	2
Ireland=>United Kingdom	0.01880	0.98140	
United States=>Ireland	25.44800	0.00000	3
Ireland=>United States	0.90230	0.43920	
Canada=>Ireland	15.20390	0.00000	3
Ireland=>Canada	0.61570	0.60480	
France=>Ireland	2.16490	0.11500	2
Ireland=>France	0.03980	0.96100	
Germany=>Ireland	4.98460	0.00691	2
Ireland=>Germany	0.00691	0.26440	
Italy=>Ireland	3.75810	0.02346	2
Ireland=>Italy	0.50150	0.60570	
Japan=>Ireland	0.03510	0.96550	2
Ireland=>Japan	82.76850	0.00000	
Brazil=>Ireland	25.72070	0.00000	1
Ireland=>Brazil	1.13310	0.28720	
China=>Ireland	1.48640	0.22290	1
Ireland=>China	21.95970	0.00000	
India=>Ireland	0.03390	0.96660	2
Ireland=>India	5.77890	0.00314	
Russia=>Ireland	0.03640	0.84870	1
Ireland=>Russia	1.86040	0.17270	
Spain=>Ireland	1.03050	0.39000	4
Ireland=>Spain	1.49410	0.20130	
Portugal=>Ireland	4.71090	0.03007	1
Ireland=>Portugal	0.63480	0.42570	
Greece=>Ireland	2.18750	0.11240	2
Ireland=>Greece	1.30130	0.27240	

4.2 Asian Crisis

4.2.1 Date Requirement (Asian Crisis)

Eurozone Crisis has happened in the developed countries and spillover to the global markets, but it is not enough that we need another crisis to compare with Eurozone Crisis. Aim at this, Asian Crisis happened in 1997 is a reasonable decision that the crisis came from Thailand and transmit to the whole world speedily.

As pointed out earlier, the first process is to build E-GARCH (1, 1) VaR model for selected stock indices. The data is still the daily stock close prices with log returns, which are from January 1st 1997 to December 31st 1999 obtained from DataStream that covers the Asian Crisis. Our samples include three types of stock indices. The developed markets (G7 groups: US Dow Jones Industrial Average, Canada S&P/TSX Composite Index, France CAC 40, Germany DAX, Italy FTSE MIB, UK FTSE 100 and Japan Nikkei 225) and emerging markets (the four countries of BRICs: Brazil Ibovespa, India BSE SENSEX, China SSE Composite Index and Russia RTS Index) stock indices stay the same, while benchmark markets stock indices are changed (the countries suffer the most loss in the Asian Crisis: Indonesia JSX Composite, South Korea KOSPI and Thailand SET Index).

All the plotting of stock indices in the Asian Crisis are shown in the appendix (from Figure 31 to Figure 44), while the plotting of returns are shown in the appendix as well (from Figure 45 to Figure 58).

4.2.2 Data Description (Asian Crisis)

As same as Eurozone Crisis, Augmented Dickey-Fuller test (ADF) indicates that (Table 16) all the selected stock indices of the Asian Crisis with log returns are stationary, since all the p-values are under 0.05.

Table 16 Augmented Dickey-Fuller test (Asian Crisis)

Test / Sample	Unit Root (ADF test)			
	statistics	p-value	Critical Values	
United Kingdom	-17.26300	0.00000	1% level	-3.43000
United States	-8.89480	0.00000	5% level	-2.86000
Canada	-14.04040	0.00000	10% level	-2.57000
France	-11.34830	0.00000		
Germany	-19.83790	0.00000		
Italy	-8.63470	0.00000		
Japan	-16.30660	0.00000		
Brazil	-6.66620	0.00000		
China	-12.62290	0.00000		
India	-13.37860	0.00000		
Russia	-17.06510	0.00000		
Indonesia	-15.85790	0.00000		
South Korea	-9.01690	0.00000		
Thailand	-17.32100	0.00000		

Table 17 Description of Samples (Eurozone Crisis)

Statistic / Sample	Description			
	Mean	Std. Deviation	Skewness	Kurtosis
United Kingdom	0.00067	0.01130	-0.07462	0.93819
United States	0.00091	0.01189	-0.44151	3.94583
Canada	0.00046	0.01006	-0.89229	5.44626
France	0.00129	0.01432	-0.21189	1.63125
Germany	0.00119	0.01568	-0.43206	1.65877
Italy	0.00109	0.01735	-0.15338	1.56089
Japan	-0.00004	0.01602	0.11846	1.74435
Brazil	0.00085	0.03277	0.62569	11.78025
China	0.00051	0.01755	-0.61861	5.19438
India	0.00025	0.01769	0.21546	1.80731
Russia	-0.00013	0.03813	-0.35115	3.92916
Indonesia	-0.00012	0.02711	0.32334	3.22077
South Korea	0.00050	0.02994	0.16769	0.89570
Thailand	-0.00067	0.02495	0.83102	2.36565

In the Table 17, it reflects the main features of daily log returns of the 14 indices during the Asian Crisis. The trend that significant skewness and kurtosis is not restricted to Eurozone Crisis, but is also evident for all the selected stock indices of Asian crisis. Thus, all the indices for Asian crisis tend to hold fat tails and left skewness. Considering the main features, standard Normal Distribution would not be able to fit the samples adequately in this respect.

Concretely, the statistics of Jarque-Bera (JB) test and Ljung-Box Q-statistic for selected stock indices are given in the Table 18. The null hypothesis of Normal Distribution is rejected for all the samples at any level of significance in the Jarque-Bera (JB) test that it supports the judgment of significant skewness and kurtosis. At a 95% significant level, there exists a high serial correlation in the variance for the squared series with order 7, what is tested by Ljung-Box Q-statistic.

Table 18 Description of Samples (Asian Crisis)

Statistic / Sample	Description			
	JB Statistics	JB p-value	LB Q(7)	LB p-value
United Kingdom	30.02880	0.00000	140.88440	0.00000
United States	519.68930	0.00000	74.42450	0.00000
Canada	1063.29000	0.00000	66.91600	0.00000
France	90.29350	0.00000	146.07550	0.00000
Germany	110.99970	0.00000	152.93340	0.00000
Italy	54.87560	0.00000	265.85050	0.00000
Japan	96.42640	0.00000	114.20560	0.00000
Brazil	4069.96100	0.00000	75.24120	0.00000
China	936.33800	0.00000	116.34060	0.00000
India	89.36540	0.00000	16.09820	0.02423
Russia	523.71940	0.00000	83.82890	0.00000
Indonesia	283.54020	0.00000	30.06630	0.00009
South Korea	24.04210	0.00001	83.66890	0.00000
Thailand	258.10760	0.00000	80.44710	0.00000

4.2.3 Estimation of E-GARCH VaR Models (Asian Crisis)

The second process is to fit E-GARCH (1, 1) Model for all the selected stock indices, where the confidence level to evaluate the performance of assumption here is 95% as well as the Eurozone Crisis. In Table 19 and Table 20, parameter values for fitting E-GARCH (1, 1) VaR models with Generalized Error Distribution (GED) have shown in the first row of each stock index, while the second row presents the p-values for different parameters.

As the results in Table 19 and Table 20, the parameters are estimated by the model of E-GARCH (1, 1) under the Generalized Error Distribution (GED). There are several indices have not passed the 95% confidence level with some parameters, such like the stock indices of Japan, China, India and South Korea, which brings doubts on the assumptions of choosing distribution and model. This will be discussed in Backtesting Section and Limitation Section later.

Table 19 E-GARCH Model Parameters 1-2 (Asian Crisis)

Estimate / Sample	E-GARCH Model Parameters			
	Mean	AR Term	MA Term	Constant
United Kingdom	0.00065	-0.17174	0.29090	-0.15250
	0.06383	0.25143	0.04202	0.00000
United States	0.00079	0.08965	-0.07353	-0.70033
	0.03614	0.51359	0.59263	0.00000
Canada	0.00098	-0.11836	0.33748	-0.37103
	0.00096	0.18371	0.00007	0.00070
France	0.00133	0.09066	-0.00789	-0.34091
	0.00009	0.00268	0.60587	0.00000
Germany	0.00175	-0.15215	0.20758	-0.35410
	0.00195	0.02340	0.00112	0.00000
Italy	0.00148	0.96507	-0.91714	-0.33714
	0.12627	0.00000	0.00000	0.01419
Japan	-0.00004	0.38407	-0.45564	-0.22923
	0.72469	0.00000	0.00000	0.00000
Brazil	0.00184	0.35796	-0.28043	-0.53965
	0.02502	0.00000	0.00000	0.00004
China	0.00000	0.23988	-0.23988	-1.05014
	0.99948	0.00000	0.00000	0.00046
India	0.00003	-0.42194	0.51416	-1.41254
	0.96391	0.42473	0.29524	0.01537
Russia	0.00071	0.40417	-0.23401	-0.82232
	0.08415	0.00000	0.00002	0.00195
Indonesia	-0.00198	0.19687	-0.07442	-0.81062
	0.00001	0.00000	0.00655	0.01591
South Korea	-0.00011	-0.26295	0.39256	-0.19589
	0.75815	0.00398	0.00004	0.00495
Thailand	-0.00302	0.42572	-0.30422	-2.41303
	0.00440	0.00000	0.00134	0.04782

Table 20 E-GARCH Model Parameters 2-2 (Asian Crisis)

Estimate / Sample	E-GARCH Model Parameters				
	ARCH Term	GARCH Term	Asymmetry Term	Shape	Log-Likelihood
United Kingdom	-0.08549	0.98335	0.08682	1.72883	2457.50200
	0.00000	0.00000	0.00000	0.00000	
United States	-0.19182	0.92257	0.08465	1.65179	2341.98600
	0.00000	0.00000	0.00000	0.00000	
Canada	-0.10239	0.96114	0.14224	1.30120	2559.11500
	0.00139	0.00000	0.18992	0.00000	
France	-0.09790	0.96058	0.09602	1.63870	2179.90400
	0.00000	0.00000	0.00010	0.00000	
Germany	-0.09228	0.95865	0.14267	1.66337	2125.78800
	0.00012	0.00000	0.00013	0.00000	
Italy	-0.07945	0.96016	0.28294	1.76276	1414.42600
	0.03783	0.00000	0.00000	0.00000	
Japan	-0.07182	0.97301	0.13463	1.54228	2057.76400
	0.00091	0.00000	0.01080	0.00000	
Brazil	-0.23511	0.92852	0.27329	1.57810	1579.88300
	0.00000	0.00000	0.00000	0.00000	
China	-0.06898	0.87362	0.52965	0.93458	2208.18700
	0.12281	0.00000	0.00000	0.00000	
India	-0.13104	0.82597	0.12199	1.60997	1619.56300
	0.00139	0.00000	0.04727	0.00000	
Russia	-0.03282	0.87867	0.47933	1.20101	1568.97900
	0.43239	0.00000	0.00000	0.00000	
Indonesia	-0.10893	0.88954	0.46216	1.04149	1459.35400
	0.02528	0.00000	0.00000	0.00000	
South Korea	-0.01290	0.97239	0.19836	1.35651	1335.90500
	0.62674	0.00000	0.00003	0.00000	
Thailand	0.08008	0.67915	0.33261	1.31912	1727.97100
	0.24526	0.00003	0.00018	0.00000	

Ljung-Box Q-statistics test is generated for both Standardized Residuals and Standardized Squared Residuals with 1, 5 and 9 lags to check whether the model has collected all the necessary information. Table 21 presents the Ljung-Box Q-statistics for Standardized Residuals of the selected stock indices at a 95% significant level. The majority of the samples cannot reject the null hypothesis of randomness with 1, 5 and 9 lags, while France CAC 40 with 5 and 9 lags can reject the null hypothesis that France CAC 40 might have autocorrelation from the samples. This condition is not confined to France CAC 40, but is also significant for Russia RTS Index (with 1, 5 and 9 lags), Indonesia JSX Composite (with 1, 5 and 9 lags) and Thailand SET Index (with 1 and 5 lags). These stock indices have not shown independent distribution, where there might exist autocorrelations from the samples.

It seems that E-GARCH (1, 1) VaR model with Generalized Error Distribution (GED) does not fit all the selected stock indices very well, but Ljung-Box Q-statistics test for Standardized Squared Residuals and Weighted ARCH Lagrange Multiplier Test reflect different results. When focus on Ljung-Box Q-statistics test for Standardized Squared Residuals, all the samples cannot reject the null hypothesis of randomness, except for China SSE Composite Index (Table 22). What's more, Table 23 supports the results of Ljung-Box Q-statistics test for Standardized Squared Residuals that only Japan Nikkei 225 with 3 lags can reject the null hypothesis of no ARCH effect (p-value is 0.03695), while all the others cannot reject the null hypothesis by applying a 95% confidence level (Table 23). Generally speaking, combined with other evidences, the residuals left are white noise, which means all valuable information has been collected. Thus, E-GARCH (1, 1) VaR model with Generalized Error Distribution (GED) can fit selected stock indices in Asian crisis adequately.

Table 21 E-GARCH Model Tests 1-3 (Asian Crisis)

Test / Sample	E-GARCH Model Tests		
	LB Test on Standardized Residuals		
	lag=1	lag=5	lag=9
United Kingdom	0.23840	3.67810	7.95160
	0.62536	0.14237	0.06007
United States	0.03571	2.48249	5.42972
	0.85010	0.78790	0.36110
Canada	0.04446	2.91144	5.64108
	0.83300	0.52830	0.31970
France	0.09053	4.39816	8.70511
	0.76350	0.02242	0.03122
Germany	0.19600	0.71340	1.30680
	0.65800	1.00000	0.99880
Italy	0.93370	2.52880	4.21990
	0.33390	0.76320	0.63880
Japan	0.00132	2.73952	4.35470
	0.97110	0.63820	0.60630
Brazil	0.76370	2.46730	4.65970
	0.38220	0.79580	0.53300
China	1.06200	3.22100	4.47300
	0.30280	0.34070	0.57770
India	0.03669	1.24987	4.83340
	0.84810	0.99980	0.49200
Russia	4.86200	7.06300	9.88900
	0.02745	0.00000	0.01028
Indonesia	6.28100	7.56600	8.26400
	0.01221	0.00000	0.04606
South Korea	0.58740	1.28060	3.31910
	0.44340	0.99970	0.83660
Thailand	4.54900	4.68800	5.19900
	0.03295	0.00925	0.40945

Table 22 E-GARCH Model Tests 2-3 (Asian Crisis)

Test / Sample	E-GARCH Model Tests		
	LB Test on Standardized Squared Residuals		
	lag=1	lag=5	lag=9
United Kingdom	1.10900	2.38300	3.67600
	0.29220	0.53100	0.64410
United States	0.18990	2.17490	3.31970
	0.66300	0.57770	0.70520
Canada	0.21850	0.75280	1.33200
	0.64020	0.91260	0.96820
France	0.14350	0.75410	2.79680
	0.70490	0.91230	0.79200
Germany	3.15200	4.00500	5.77200
	0.07584	0.25341	0.32529
Italy	0.51130	1.29620	4.51960
	0.47460	0.78980	0.50320
Japan	0.91480	4.40810	6.55240
	0.33880	0.20740	0.23960
Brazil	0.91010	3.46170	4.63300
	0.34010	0.32920	0.48520
China	11.49000	13.45000	14.48000
	0.00070	0.00115	0.00477
India	0.08551	0.64175	1.50906
	0.77000	0.93380	0.95480
Russia	0.07013	0.48276	2.56812
	0.79110	0.96030	0.82750
Indonesia	0.16930	0.39290	0.73560
	0.68070	0.97290	0.99470
South Korea	0.00258	0.66081	2.22413
	0.95950	0.93030	0.87660
Thailand	0.25250	3.47340	5.03870
	0.61530	0.32740	0.42370

Table 23 E-GARCH Model Tests 3-3 (Asian Crisis)

Test / Sample	E-GARCH Model Tests		
	Weighted ARCH LM Tests		
	lag=1	lag=5	lag=9
United Kingdom	0.31460	2.50510	2.79990
	0.57490	0.37010	0.55210
United States	0.85470	2.38280	2.89990
	0.35520	0.39270	0.53270
Canada	0.14900	0.55850	0.98360
	0.69950	0.86620	0.91620
France	0.72180	0.94130	2.86760
	0.39560	0.75040	0.53890
Germany	0.31380	1.39290	2.85880
	0.57530	0.62090	0.54060
Italy	0.20250	1.36180	4.75540
	0.65270	0.62940	0.25040
Japan	4.35300	5.64800	6.63300
	0.03695	0.07264	0.10404
Brazil	0.99730	1.19360	1.31620
	0.31800	0.67650	0.85740
China	0.05566	1.05500	1.38437
	0.81350	0.71670	0.84420
India	0.01199	0.93618	1.51114
	0.91280	0.75200	0.81910
Russia	0.15680	0.69580	2.04520
	0.69210	0.82470	0.70780
Indonesia	0.10210	0.42950	0.53200
	0.74930	0.90420	0.97540
South Korea	0.50280	1.25160	2.61100
	0.47830	0.66000	0.58980
Thailand	3.43200	4.84000	5.45200
	0.06396	0.11189	0.18263

4.2.4 Backtesting (Asian Crisis)

After estimating E-GARCH (1, 1) VaR model with Generalized Error Distribution (GED), backtesting should be taken into account as a critical part of risk measurement. Model validation should be checked by Unconditional Coverage Test (Kupiec) as well as Conditional Coverage Test (Christoffersen). Definitely, the confidence level applied in the tests is still at 95% level.

The violations of selected stock indices are listed in the Table 24 that actual exceedances are fairly closed to expected exceedances. Although actual exceedances of some stock indices are more than expected exceedances, Unconditional Coverage Test (Kupiec) and Conditional Coverage Test (Christoffersen) would put the model validation into evaluation to judge whether the exceedances are correct.

In the Table 25, most samples cannot reject the null hypothesis of correct exeedances that the model is valid for most selected stock indices. However, both Indonesia JSX Composite (p-values are 0.04792 for Kupiec and 0.01403 for Christoffersen) and Thailand SET Index (p-values are 0.00047 for Kupiec and 0.00166 for Christoffersen) reject the null hypothesis for both tests. It is interesting that both the counties suffered the most loss in the Asian crisis, and the indices of these two counties have sharp drops in returns and fat tails in volatility. E-GARCH (1, 1) model with Generalized Error Distribution (GED) might not be able to cover all the features these samples required, so changing for other GARCH model (other GARCH orders and other GARCH family members) or other skewed distribution (Skewed Student-t distribution, Skewed Generalized Error distribution and so on) may improve the results. The further explanation would be discussed in Limitation section.

In general, E-GARCH (1, 1) model with Generalized Error Distribution (GED) is still a valid model for the majority of samples to predict volatility accurately for VaR values.

Table 24 E-GARCH Model Exceedances (Asian Crisis)

Sample \ Test	Backtesting	
	Expected Exceedances	Actual Exceedances
United Kingdom	39	43
United States	37	43
Canada	38	39
France	37	44
Germany	37	48
Italy	25	29
Japan	36	42
Brazil	34	39
China	39	30
India	30	23
Russia	39	32
Indonesia	31	21
South Korea	30	27
Thailand	36	18

Table 25 E-GARCH Model Backtesting (Asian Crisis)

Sample \ Test	Backtesting			
	Unconditional Coverage Tests		Conditional Coverage Tests	
	Likelihood Ratio statistic	p-value	Likelihood Ratio statistic	p-value
United Kingdom	0.39719	0.52855	0.46425	0.79285
United States	0.72237	0.39537	0.82045	0.66350
Canada	0.00551	0.94083	0.00585	0.99708
France	1.08984	0.29651	3.16802	0.20515
Germany	2.79505	0.09456	3.27157	0.19480
Italy	0.49977	0.47960	3.29446	0.19258
Japan	0.74120	0.38928	0.93320	0.62713
Brazil	0.58025	0.44621	1.48844	0.47510
China	2.41551	0.12014	1.18924	0.55177
India	2.13974	0.14353	2.16073	0.33947
Russia	1.44290	0.22967	1.78600	0.40943
Indonesia	3.91283	0.04792	8.53289	0.01403
South Korea	0.50115	0.47900	1.01451	0.60215
Thailand	12.25049	0.00047	12.80362	0.00166

Note: Unconditional Coverage Test Null Hypothesis (Kupiec): Correct Exceedances; Conditional Coverage Test (Christoffersen) Null Hypothesis: Correct Exceedances & Independent

4.2.5 Granger Causality Test (Asian Crisis)

The final process is to check whether there exists contagion risk among the selected stock markets. Indonesia JSX Composite, South Korea KOSPI and Thailand SET Index are the benchmark indices to compare with developed markets as well as emerging markets because of the most loss that Indonesia, South Korea and Thailand suffered in Asian crisis. Note that a 95%confidence level is still applied in Granger Causality Test, while the lag value in each test is selected with minimum Akaike Information Criterion (AIC) value.

4.2.5.1 Granger Causality Test for Indonesia JSX Composite

The null hypothesis here, that former index does not Granger cause the latter one (United Kingdom=> Indonesia means that United Kingdom FTSE 100 does not Granger cause Indonesia JSX Composite), is evaluated at confidence level of 95%, while p-values are also listed.

As it is shown in Table 26, there are nine stock indices (UK FTSE 100, US Dow Jones Industrial Average, Canada S&P/TSX Composite Index, France CAC 40, Germany DAX, Italy FTSE MIB, Brazil Ibovespa, India BSE SENSEX, South Korea KOSPI) can Granger cause Indonesia JSX Composite, but the volatility of Indonesia JSX Composite is not responsible for their negative shocks. It is clear that Russia RTS Index and Thailand SET Index reject the null hypothesis, which indicates they are the Granger causes for Indonesia JSX Composite, while Indonesia JSX Composite can also be the Granger cause for each of them. In fact, two sides have significant interactions. Finally, there is no significant extreme contagion effect between other stock indices groups, since the p-values are over 0.05 and cannot reject the null hypothesis. Note that Indonesia JSX Composite cannot influence other stock indices without interaction. The reason is that Indonesia might be the victim and transmitter in the Asian crisis rather than the originator.

Table 26 Granger Causality Test for Indonesia (Asian Crisis)

Samples \ Cause	Indonesia		
	Statistics	p-value	Lag
United Kingdom=>Indonesia	19.42040	0.00001	1
Indonesia=>United Kingdom	0.25590	0.61300	
United States=>Indonesia	53.92180	0.00000	1
Indonesia=>United States	1.97260	0.16040	
Canada=>Indonesia	52.58780	0.00000	1
Indonesia=>Canada	1.23520	0.26660	
France=>Indonesia	23.57120	0.00000	1
Indonesia=>France	0.00360	0.95200	
Germany=>Indonesia	16.54610	0.00005	1
Indonesia=>Germany	0.69300	0.40530	
Italy=>Indonesia	4.70050	0.03040	1
Indonesia=>Italy	0.04240	0.83690	
Japan=>Indonesia	0.89380	0.40940	2
Indonesia=>Japan	2.63850	0.07190	
Brazil=>Indonesia	39.33260	0.00000	1
Indonesia=>Brazil	2.23930	0.13480	
China=>Indonesia	1.13970	0.33180	3
Indonesia=>China	1.66670	0.17240	
India=>Indonesia	4.72820	0.02987	1
Indonesia=>India	0.38800	0.53350	
Russia=>Indonesia	3.34010	0.03576	2
Indonesia=>Russia	4.55280	0.01072	
South Korea=>Indonesia	9.50600	0.00000	5
Indonesia=>South Korea	0.35370	0.88000	
Thailand=>Indonesia	9.39010	0.00223	1
Indonesia=>Thailand	8.07010	0.00458	

4.2.5.2 Granger Causality Test for South Korea KOSPI

The similar trend is presented by South Korea KOSPI. Table 27 indicates the Granger Causality Test statistics for South Korea KOSPI at a 95% significant level, along with the p-values. When negative downside shifts come in these seven stock indices (UK FTSE 100, US Dow Jones Industrial Average, Canada S&P/TSX Composite Index, France CAC 40, Germany DAX, Brazil Ibovespa and Russia RTS Index), their volatilities would help to understand and forecast the shocks of South Korea KOSPI, as these stock indices can Granger cause South Korea KOSPI. Additionally, Thailand SET Index can reject the null hypothesis (p-value is 0.00117), and South Korea KOSPI can Granger cause Thailand SET Index as well (p-value is 0.00684). Two sides are influenced and Granger caused each other. Among the samples, South Korea KOSPI can only be the Granger cause for Indonesia JSX Composite at a 95% confidence level.

Table 27 Granger Causality Test for South Korea (Asian Crisis)

Cause / Samples	South Korea		
	Statistics	p-value	Lag
United Kingdom=>South Korea	21.05640	0.00000	1
South Korea=>United Kingdom	2.06260	0.15120	
United States=>South Korea	23.01890	0.00000	1
South Korea=>United States	0.20190	0.65330	
Canada=>South Korea	21.56160	0.00000	1
South Korea=>Canada	1.40270	0.23650	
France=>South Korea	9.97170	0.00163	1
South Korea=>France	1.17180	0.27930	
Germany=>South Korea	6.22350	0.01274	1
South Korea=>Germany	0.25150	0.61610	
Italy=>South Korea	3.69100	0.05500	1
South Korea=>Italy	0.00400	0.94930	
Japan=>South Korea	1.78730	0.16790	2
South Korea=>Japan	1.74980	0.17430	
Brazil=>South Korea	13.28130	0.00028	1
South Korea=>Brazil	1.52730	0.21680	
China=>South Korea	0.29790	0.82690	3
South Korea=>China	0.60420	0.61230	
India=>South Korea	0.00110	0.97380	1
South Korea=>India	1.25280	0.26330	
Russia=>South Korea	5.16470	0.02322	1
South Korea=>Russia	0.48790	0.48500	
Indonesia=>South Korea	0.35370	0.88000	5
South Korea=>Indonesia	9.50600	0.00000	
Thailand=>South Korea	6.79420	0.00117	2
South Korea=>Thailand	5.00710	0.00684	

4.2.5.3 Granger Causality Test for Thailand SET Index

The Asian crisis began with the currency shocks in Thailand and transmitted to the global market quickly in 1997. Therefore, Thailand SET Index has particular meaning for studying the contagion risk. In the Table 28, Granger Causality Test statistics for Thailand SET Index point out that UK FTSE 100, US Dow Jones Industrial Average, Canada S&P/TSX Composite Index, France CAC 40, Germany DAX, Italy FTSE MIB and Russia RTS Index can reject the null hypothesis at the confidence level of 95% level. That means significant declines in these markets could help to forecast the extreme downside shifts for Thailand SET Index. As mentioned before, Indonesia JSX Composite and South Korea KOSPI can Granger cause Thailand SET Index, while Thailand SET Index can also be Granger cause for them. There is no significant contagion effect between Thailand and other Asian countries, especially for China, Japan and India.

Table 28 Granger Causality Test for Thailand (Asian Crisis)

Samples \ Cause	Thailand		
	Statistics	p-value	Lag
United Kingdom=>Thailand	7.50930	0.00057	2
Thailand=>United Kingdom	0.41550	0.66010	
United States=>Thailand	22.02820	0.00000	1
Thailand=>United States	1.52610	0.21690	
Canada=>Thailand	33.08880	0.00000	1
Thailand=>Canada	0.38380	0.53570	
France=>Thailand	13.36440	0.00027	1
Thailand=>France	0.06490	0.79900	
Germany=>Thailand	6.50360	0.00154	2
Thailand=>Germany	0.68740	0.50300	
Italy=>Thailand	9.20810	0.00248	1
Thailand=>Italy	0.03770	0.84620	
Japan=>Thailand	0.12810	0.87980	2
Thailand=>Japan	2.01520	0.13370	
Brazil=>Thailand	2.72620	0.09894	1
Thailand=>Brazil	0.11500	0.73460	
China=>Thailand	1.61740	0.18350	3
Thailand=>China	0.87280	0.45450	
India=>Thailand	3.00590	0.08323	1
Thailand=>India	0.02090	0.88500	
Russia=>Thailand	12.72620	0.00037	1
Thailand=>Russia	0.01410	0.90550	
Indonesia=>Thailand	8.07010	0.00458	1
Thailand=>Indonesia	9.39010	0.00223	
South Korea=>Thailand	5.00710	0.00684	2
Thailand=>South Korea	6.79420	0.00117	

4.3 Discussion

Generally speaking, the results confirm that the validation of E-GARCH (1, 1) VaR model under Generalized Error Distribution (GED) can cover most stock indices in both Eurozone Crisis and Asian Crisis samples. Though the model is valid, some selected stock indices still reflect inadaptability in this study.

For instance, the parameters of Spain IBEX 35 in the Eurozone Crisis are not statistically significant to reject the null hypothesis that Mean, AR Term and MA Term indicate too large errors after modelling possibly (Table 5). Weighted ARCH Lagrange Multiplier Test supports this indication that Spain IBEX 35 cannot reject the null hypothesis with 5 and 7 lags, which means the residuals of Spain IBEX 35 are not white noise after modelling (Table 9). Another sample with problem is Canada S&P/TSX Composite Index that the only one cannot pass backtesting in the Eurozone Crisis. To be more specific, Canada S&P/TSX Composite Index indicates existing ARCH effect in the Ljung-Box Q-statistics Test on Standardized Squared Residuals (Table 8). As a consequence, it has rejected the null hypothesis for both tests in the backtesting that p-values are 0.00651 for Kupiec and 0.00087 for Christoffersen (Table 11). Unfortunately, this condition is not only limited to the samples in the Eurozone Crisis, but also expands to Indonesia JSX Composite and Thailand SET Index in the Asian Crisis (Table 21 and Table 25). It means that E-GARCH (1, 1) VaR model under Generalized Error Distribution (GED) may not be able to fit some particular stock indices adequately. This problem will be explained in the Limitation Section later.

However, it cannot be denied that the model can fit the majority of samples and give accurate forecasts. In spite of the rare indices, E-GARCH (1, 1) VaR model under Generalized Error Distribution (GED) is accepted for this study's objective.

Actually, the target of this dissertation is to find the evidence of contagion risk out, so it is essential to compare the results of both selected financial crises. The Eurozone Crisis part gives significant evidence of risk spillover, either in the developed countries or emerging markets. As shown in Table 29, developed countries could affect the benchmark countries except for Japan. The volatility of benchmark countries is responsible for partial developed countries directly, while most developed countries would affect the rises and drops of benchmark countries. However, each one of developing countries can be influenced by or interact with benchmark countries, especially for China and India (Table 29). The reason why developed and developing countries have the difference is that developed countries have advanced financial system to protect their economies, but the imperfection in financial system of emerging markets makes it easy to receive the negative shocks form the originator.

Note that benchmark countries have significant risk spillover within their benchmark group, which appears to be a regional effect. There is no denying that the whole world suffered the effect of Eurozone Crisis. When a crisis happens, it would transmit from the originator to others. Some countries may play a role as transfer point to spread the extreme downside shifts to the whole world. For example, Germany is not influenced by the volatility of Spain directly. Spain IBEX 35 would pass the extreme event to Italy FTSE MIB at first, and Italy FTSE MIB acts as a transfer point to spread the event to Germany financial market. Some studies regard the American and Japanese stock markets as links for European markets to spread the volatility (Blundell-Wignall and Slovik, 2011). Even though some markets are not directly linked to the financial originator, the negative shocks could still arrive on these markets. Limited by time and design, this study cannot track the spreading order, but it is a good point to develop the further research.

Table 29 Contagion Effect Summary (Eurozone Crisis)

Factor / Sample	Contagion Effect Summary	
	Be Affected by Benchmark	Affect Benchmark
United Kingdom	-	Greece, Ireland
United States	Spain	Portugal, Greece, Ireland
Canada	Portugal	Greece, Ireland
France	-	Spain, Greece
Germany	-	Greece, Ireland
Italy	Spain	Greece, Ireland
Japan	Spain, Portugal, Greece, Ireland	-
Brazil	Spain, Portugal	Greece, Ireland
China	Spain, Portugal, Greece, Ireland	-
India	Spain, Portugal, Greece, Ireland	-
Russia	Spain, Portugal	-
Spain	-	Portugal, Greece
Portugal	Spain, Greece	Ireland
Greece	Spain	Portugal
Ireland	Portugal	-

Note: Be affected by benchmark item includes the results influenced by and interact with benchmark countries.

However, the contagion effect summary for Asian Crisis is totally different. None of the G7 group is affected by benchmark countries in the Asian Crisis, whereas all the developed countries can Granger cause the negative shifts in the benchmark countries except for Japan (Table 30). Even in the group of developing countries, only Russia RTS Index could interact with Indonesia JSX Composite stock index at a significant level to reflect the contagion effect, but most of them could affect the volatility of benchmark countries (Table 30). The extreme negative shifts in benchmark group do not affect the other markets although benchmark group is sensitive to all the selected stock indices analysed. As we know, the Asian Crisis in 1997 swept the world rapidly after it happened. So many countries were involved into this event and suffered big loss. Probably the explanation for the results is because the crisis spread and transmitted to the whole world through transfer point, such as Russia or other correlated countries. There is no doubt that the contagion effect exists in the Asian Crisis, since significant evidence of interaction between the benchmark countries. Table 30 indicates that the contagion risk is also detected in the Asian Crisis.

Table 30 Contagion Effect Summary (Asian Crisis)

Factor / Sample	Contagion Effect Summary	
	Be Affected by Benchmark	Affect Benchmark
United Kingdom	-	Indonesia, South Korea, Thailand
United States	-	Indonesia, South Korea, Thailand
Canada	-	Indonesia, South Korea, Thailand
France	-	Indonesia, South Korea, Thailand
Germany	-	Indonesia, South Korea, Thailand
Italy	-	Indonesia, Thailand
Japan	-	-
Brazil	-	Indonesia, South Korea
China	-	-
India	-	Indonesia
Russia	Indonesia	South Korea, Thailand
Indonesia	South Korea, Thailand	South Korea
South Korea	Thailand	Indonesia, Thailand
Thailand	Indonesia, South Korea	Indonesia, South Korea

Note: Be affected by benchmark item includes the results influenced by and interact with benchmark countries.

Comparing the results of both Eurozone Crisis and Asian Crisis, the developed country group would affect the benchmark volatility but rare of them would be influenced directly. In contrast, emerging market group is more likely to be affected by the originator. As mentioned before, developed countries may have advanced financial system to slow the spreading and protect themselves from the crisis, whereas the developing countries might lack the financial strategy to defend the extreme downside event. Therefore, an effective financial system is necessary for each country to make the financial market stable. Regional effect is also significant within the benchmark groups that the countries would affect or interact with others in the benchmark groups. Additionally, the transmitting order of contagion risk is not discussed in this study, but it is an interesting topic to develop further research to find how the contagion risk transfer from one country to another. With the process of globalization, countries are linked closely by financial assets. Once the financial crisis happens, it would sweep the world rapidly. This study has found significant proof in the both crises that contagion risk does exist and spread when the extreme negative events come, also indicates the advanced financial system could contribute to slow the threat of risk spillover.

4.4 Limitation

Certainly, mistakes also play a role in this study. When choosing the stock indices, it would be biased by selecting some representatives rather than covering the whole markets. As shown in this dissertation, G7 group stands for the developed markets and BRICs are on behalf of the emerging markets. However, the representatives cannot stand for all the markets, especially for regional economies. For example, including all the European countries into Eurozone Crisis would have better results, because simply using developed and emerging markets may miss some significant evidences for contagion risk. A range of European countries could help to track the crisis process and transmitting order.

Another place could be improved that is the range of benchmark countries. For convince, the countries suffered the most loss or happened serious problem compose the benchmark groups.

Although there does exist significant evidence of contagion effect in this study, what the crisis originator is and how the crisis transfers into other markets could be explored for further research. With the globalization of the economy in recent decades, it would be hard to track which country opens the Pandora's Box. Simply using the countries suffered the most loss might be an arbitrary decision, and might omit the important information. One solution is to include all the samples into cause and effect analysis in turns, which could contribute to figure out the originator, process and transmitting order. Meanwhile, whether the crisis has effective order is an interesting topic for intensive study that whether the magnitude of crisis would be equal when crisis transfer from strong economic entity to weak economic entity and from weak economic entity to strong economic entity. An example would make this clear. US sub-prime mortgage market crisis rapidly spreads into the financial markets in the world, but the effect could not be the same when a crisis happens in Uruguay. Strong economic entity could have advanced financial system to slow the effect, while weak economic entity might be swamped in the mud directly. This could be an interesting topic to explore the volatility of both strong economic entity and weak economic.

On the other hand, model risk is unavoidable in this study that both distribution and GARCH order may affect the results significantly. Even though the E-GARCH (1, 1) VaR model with Generalized Error Distribution (GED) is valid for the majority of samples to predict volatility accurately, it still cannot fit some selected stock indices, such as Canada S&P/TSX composite index (p-values are 0.00651 for Kupiec and 0.00087 for Christoffersen) and Portugal PSI Geral index (p-value is 0.01768 for Kupiec) in the Eurozone Crisis; and Indonesia JSX Composite (p-values are 0.04792 for Kupiec and 0.01403 for Christoffersen) and Thailand SET Index (p-values are 0.00047 for Kupiec and 0.00166 for Christoffersen) in the Asian Crisis. This mistake hinges on both distribution and GARCH order. More exactly, other GARCH order might have better performance for some selected stock indices (Walid et al., 2011). In addition, other GARCH family members (standard GARCH, T-GARCH and I-GARCH) could also show superiority in the conditional situations. Since the samples hold apparent strong skewness and kurtosis, skewed distribution may have advantages than Generalized Error Distribution (GED). The alternatives, including Skewed Student-t

Distribution, Skewed Generalized Error Distribution and so on, would reflect better results on the Backtesting part and contribute to better predictions. However, the aim of this study is to focus on testing the contagion risk rather than evaluating the perfect model, so simply applying the E-GARCH (1, 1) VaR model with Generalized Error Distribution (GED). Further research can compare different models and distributions to find the best model for each stock index.

Limited by time and length, this dissertation cannot cover all the details particularly. According to the shortcomings, this study still provides some directions to further research. Both the range of samples and model selection can be improved in the future.

5. CONCLUSION

With the global economic integration, different financial markets around the world connect each other closely. For this reason, contagion risk is the most serious threat for the financial markets as local economy is susceptible by outside effect. When focus on successful risk management, it becomes increasingly essential to forecast, control and monitor the contagion risk. How to detect and defend the risk spillover and is meaningful for the investors' survival. Almost all the financial institutions, like insurance companies, banks, pension funds and so on, would have motivation to model market risk and should pay attention to the extreme downside interaction between the financial markets. Thus, it is important to understand the mechanism of contagion effect to guarantee effective and successful risk management and investment diversification when the negative events happen. Indeed, risk is expected to transmit from one market to another, and spread to the world at last. Large price change in one market, like the stock index change in this study, may bring similar large price shifts in other markets. Study on contagion risk contributes to build better market risk regulation, as well as control the internal risk (Baur, 2003).

This paper has studied the spread of the both current Eurozone Crisis in 2010 and Asian Crisis in 1997 to find the proof of contagion risk. Three groups of samples comprise this research that developed countries (G7 group), emerging markets (BRICs countries) and benchmark countries (Spain, Portugal and Greece for Eurozone crisis in 2010, while Indonesia, Korea and Thailand for Asian financial crisis in 1998). As to compare the contagion effect of developed countries and emerging markets, a range of stock indices from different countries are selected to bring more evidence to the issue of risk spillover. Each period under analysis covers the financial crisis correlated. All the selected stock indices suggest the presence of heteroskedasticity. To accommodate these features, E-GARCH (1, 1) VaR model with Generalized Error Distribution (GED) is applied to measure the contagion risk. In addition, model validation is conducted by Unconditional Coverage Test (Kupiec) as well as Conditional Coverage Test (Christoffersen). As expected, E-GARCH (1, 1) VaR model with Generalized Error Distribution (GED) is able to fit the majority of samples and give accurate predictions.

In conclusion, the objective of this study has been to better understand the existence and spreading process through the financial crisis, which is concerned at the detection of Granger causality in risk between the samples. The results illustrate that both developed countries and emerging markets have received significant contagion risk in the Eurozone Crisis. Especially for developing countries, they are more likely to be influenced by the benchmark group. This study also has identified contagion effect in the Asian Crisis overall. However, the results have pointed out some interesting facts that Russia RTS Index is the only one stock index that is influenced by benchmark group, whereas most selected stock indices, both developed and developing groups, can affect Granger cause the negative shifts in the benchmark countries. There is weak evidence for contagion risk, which means the volatility of benchmark countries is not responsible for the negative shifts of developed countries. Considering the evidence of Asian Crisis, one possible explanation is that some countries (like Russia) may act as transfer points to spread the extreme negative events to the global financial markets. Even though some markets cannot receive the contagion effect by benchmark group directly, the negative shocks could still arrive on these markets through these transfer points. Nonetheless, the Asian Crisis in 1997 still provides significant evidence of risk spillover between the benchmark countries.

Comparing results of both Eurozone Crisis and Asian Crisis, emerging market group is more likely to be affected by the benchmark volatility than developed country group. Advanced financial system would be the successful tool to help developed countries protect themselves from the extreme downside shocks, but the developing countries might lack the financial strategy to defend the crisis. As a consequence, building an effective financial system is very important for each country to make the local economy stable. A key point of this study is that regional effect is significant as well within the benchmark groups that regional markets with close links would affect or interact with others significantly in the benchmark groups. Generally, this study has identified exactly the existence of contagion risk in both crises and given explanation for this phenomenon.

Unfortunately, this study does not focus on the possible model errors. Limited by time, this study cannot cover all the aspects of contagion risk topic as well. Wider range of samples, appropriate GARCH model with suitable distribution may improve the modelling results and explain the rare biases. According to the shortcomings, future research could focus on the topic as transmitting order of contagion risk and appropriate model to fit selected samples.

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APPENDIX

Figure 1 Stock Index of UK FTSE 100 (Eurozone Crisis)

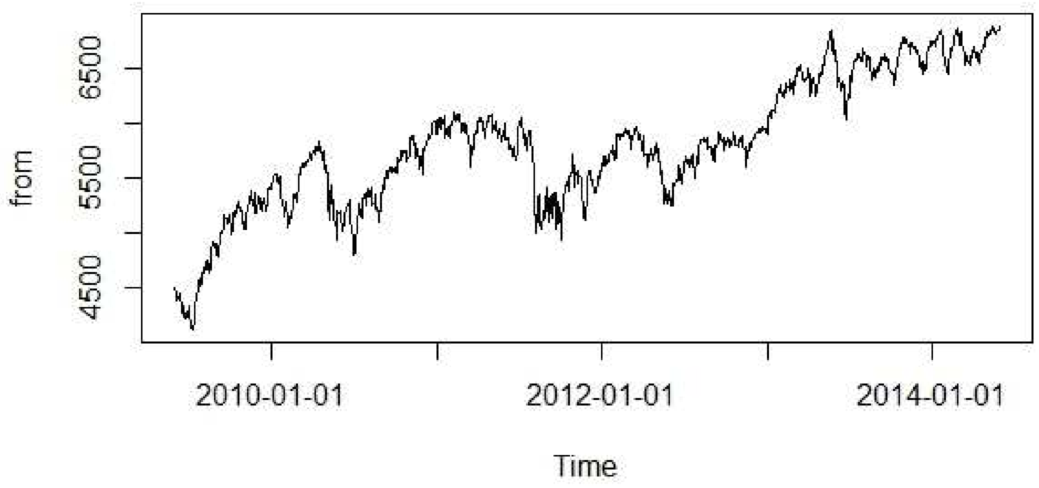

Figure 2 Stock Index of US Dow Jones Industrial Average (Eurozone Crisis)

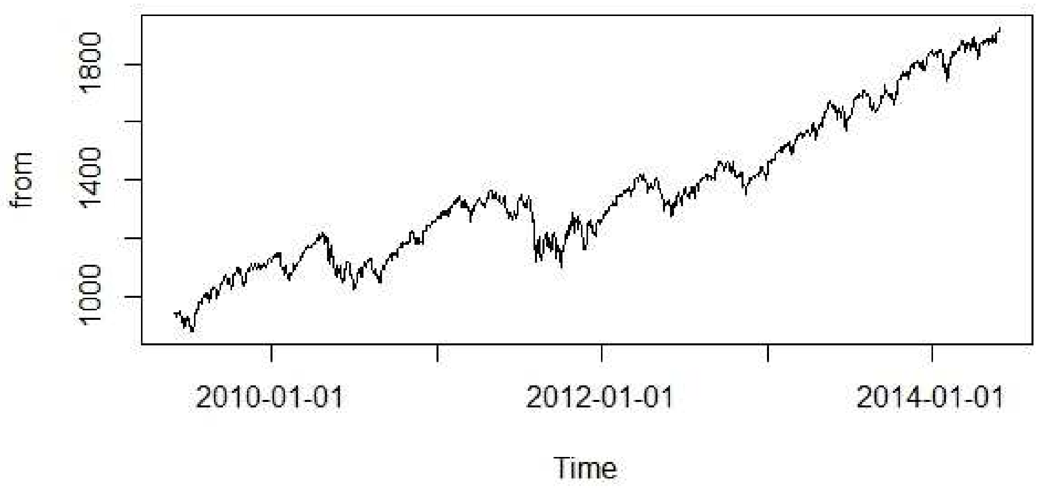

Figure 3 Stock Index of Canada S&P/TSX Composite Index (Eurozone Crisis)

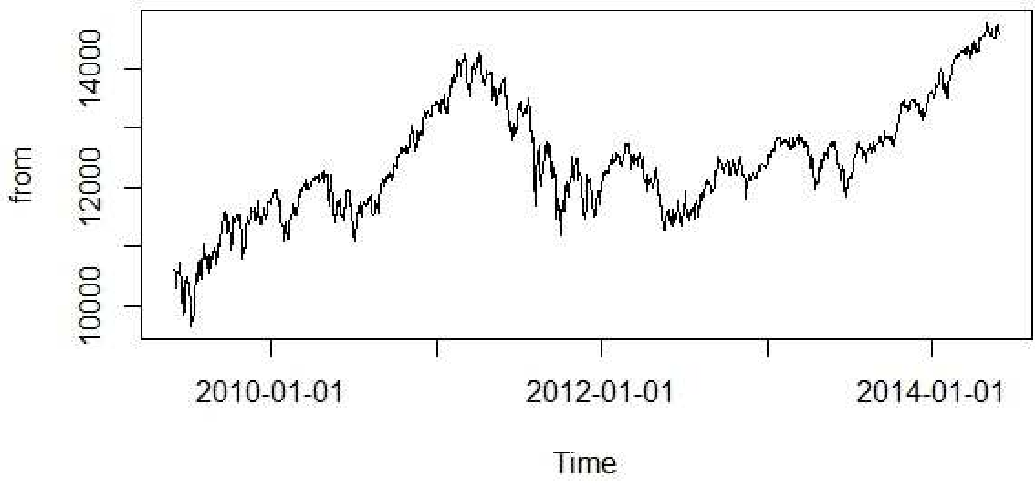

Figure 4 Stock Index of France CAC 40 (Eurozone Crisis)

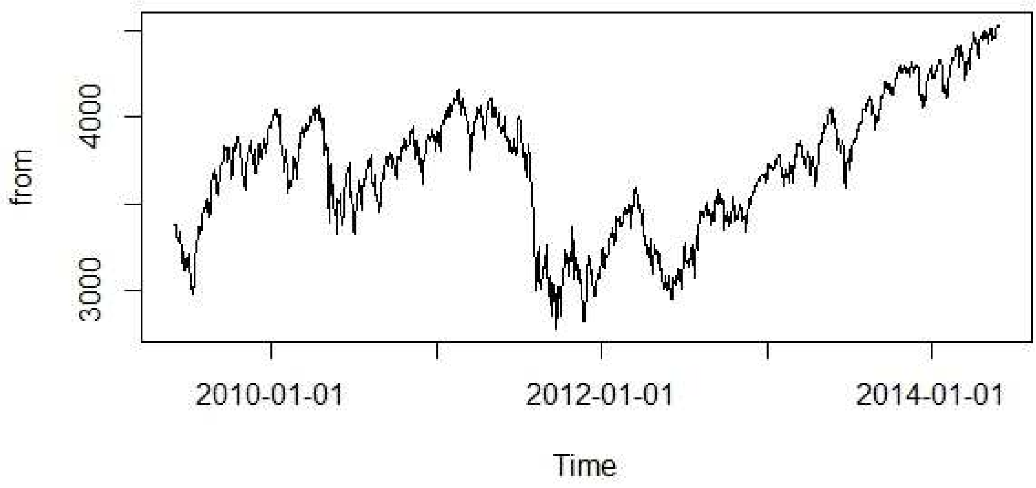

Figure 5 Stock Index of Germany DAX (Eurozone Crisis)

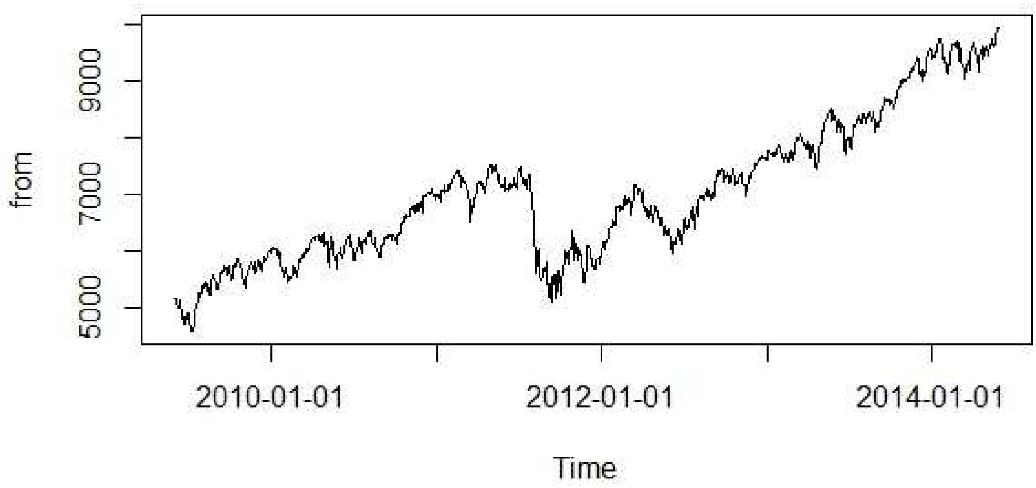

Figure 6 Stock Index of Italy FTSE MIB (Eurozone Crisis)

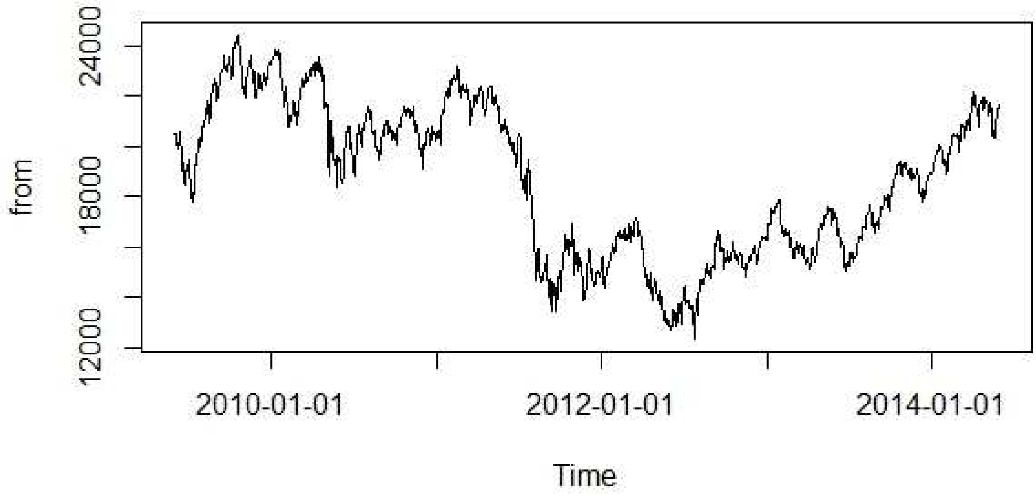

Figure 7 Stock Index of Japan Nikkei 225 (Eurozone Crisis)

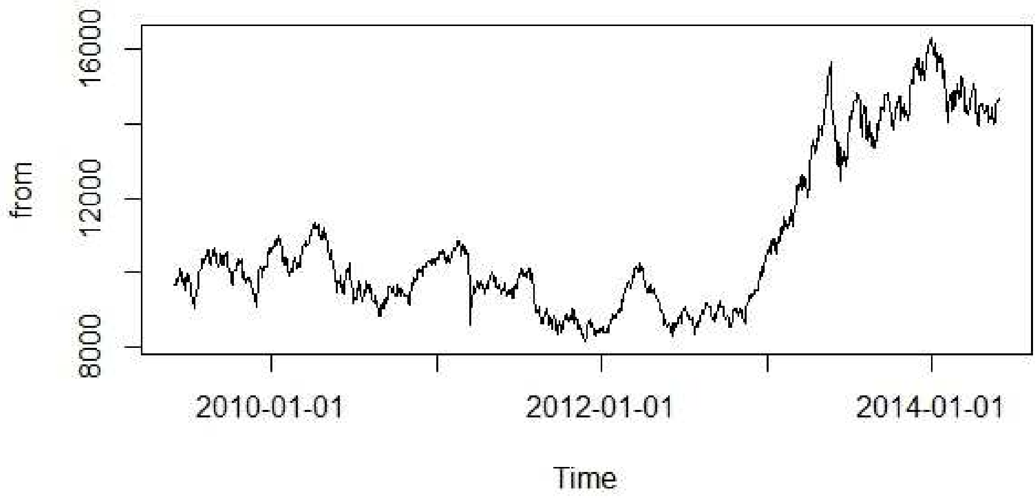

Figure 8 Stock Index of Brazil Ibovespa (Eurozone Crisis)

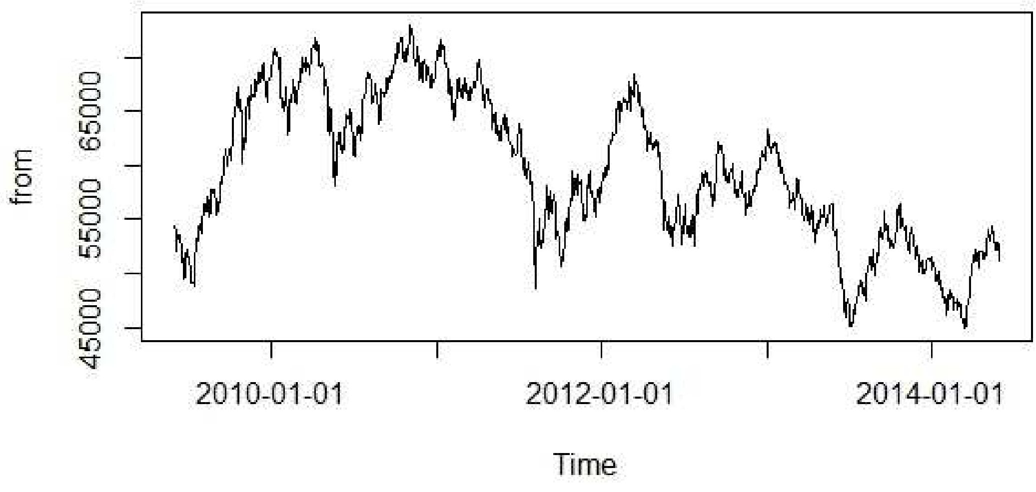

Figure 9 Stock Index of China SSE Composite Index (Eurozone Crisis)

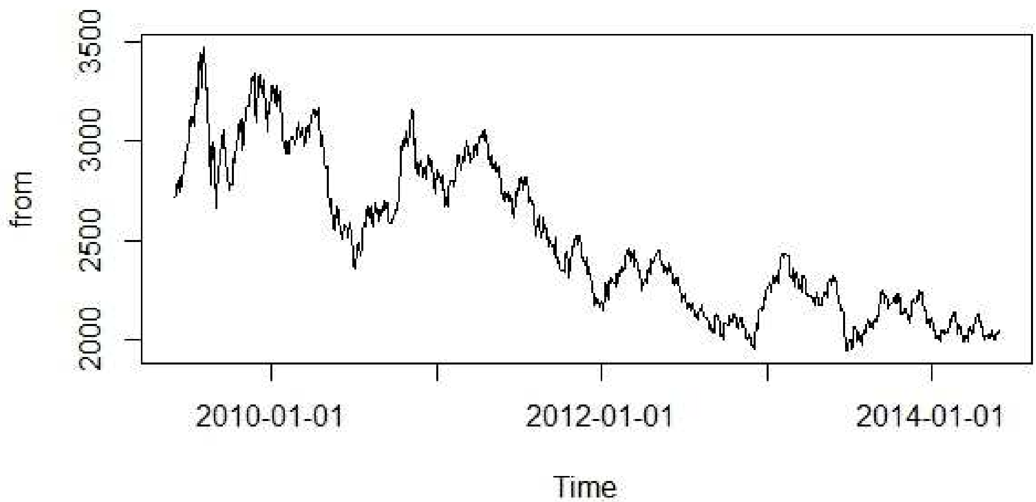

Figure 10 Stock Index of India BSE SENSEX (Eurozone Crisis)

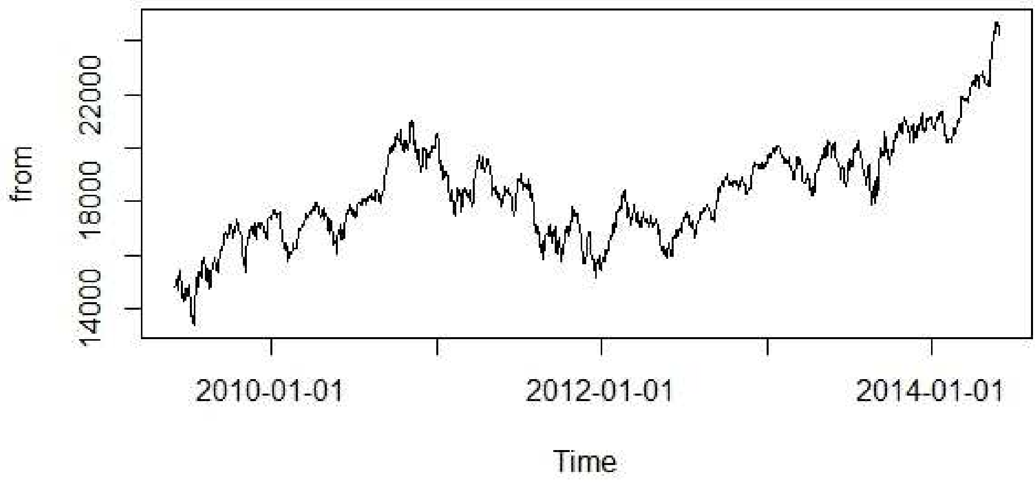

Figure 11 Stock Index of Russia RTS Index (Eurozone Crisis)

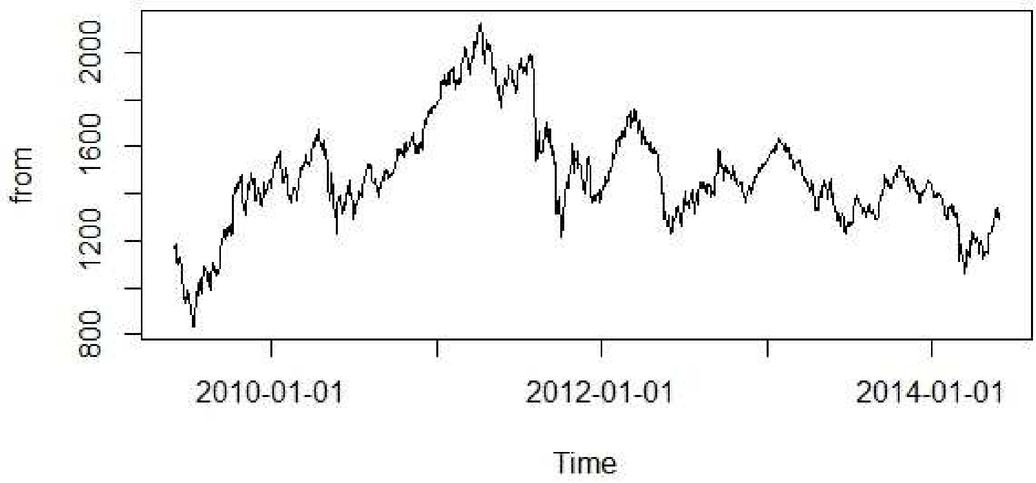

Figure 12 Stock Index of Spain IBEX 35 (Eurozone Crisis)

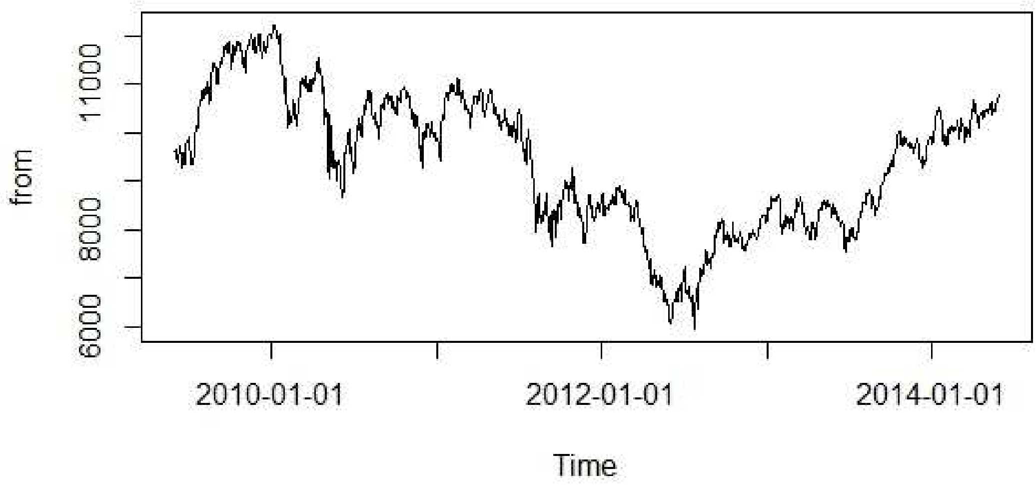

Figure 13 Stock Index of Portugal PSI Geral (Eurozone Crisis)

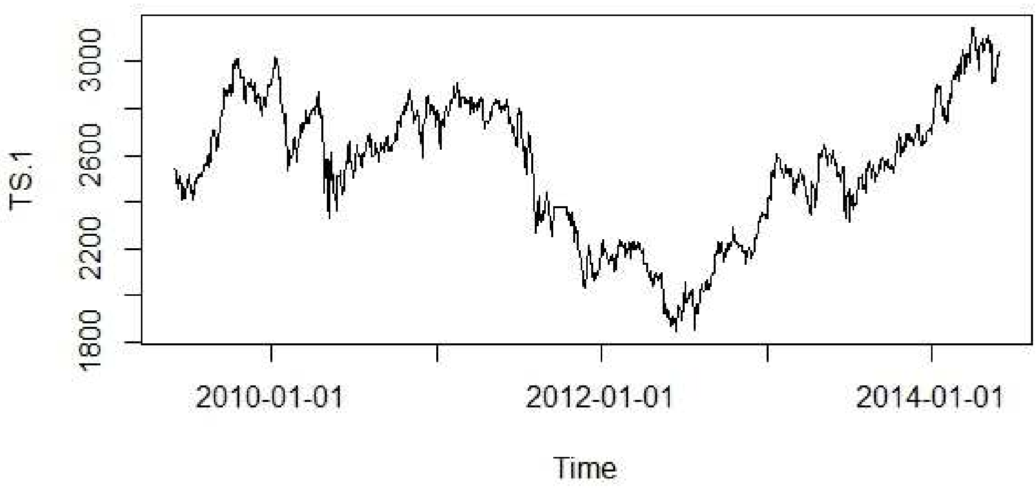

Figure 14 Stock Index of Greece FTSE/ATHEX LARGE CA (Eurozone Crisis)

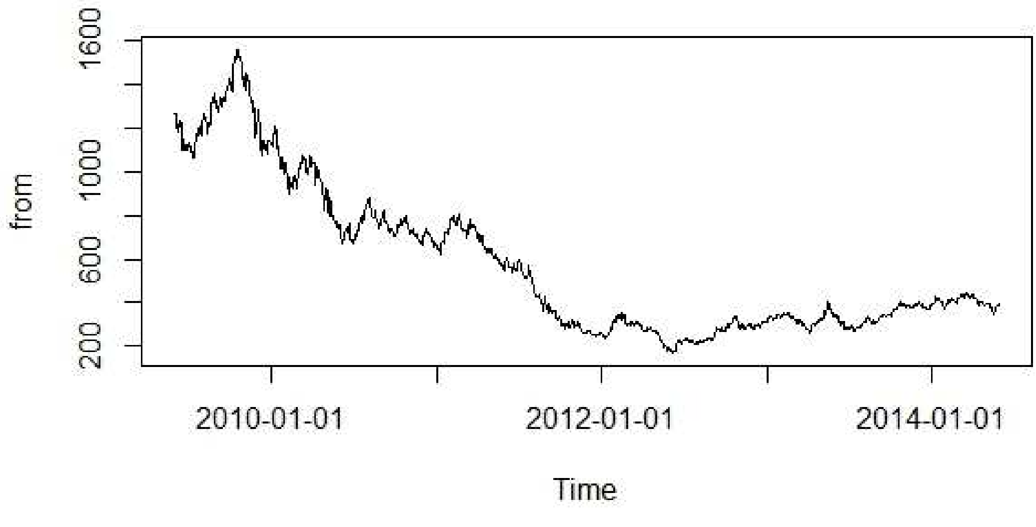

Figure 15 Stock Index of Ireland ISEQ Overall Price (Eurozone Crisis)

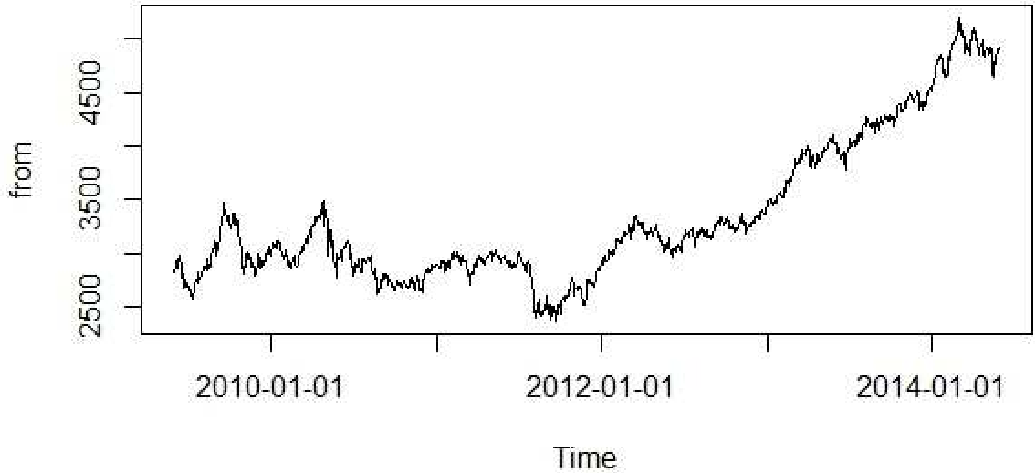

Figure 16 Returns of UK FTSE 100 (Eurozone Crisis)

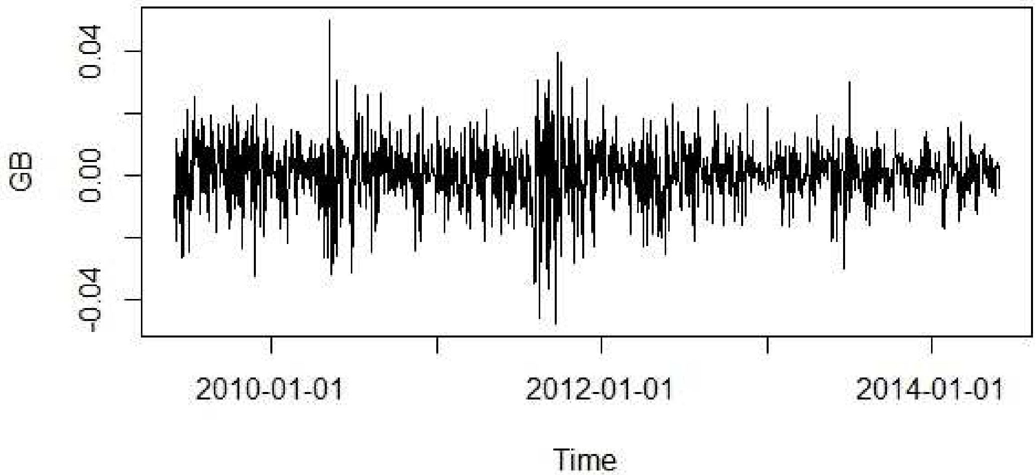

Figure 17 Returns of US Dow Jones Industrial Average (Eurozone Crisis)

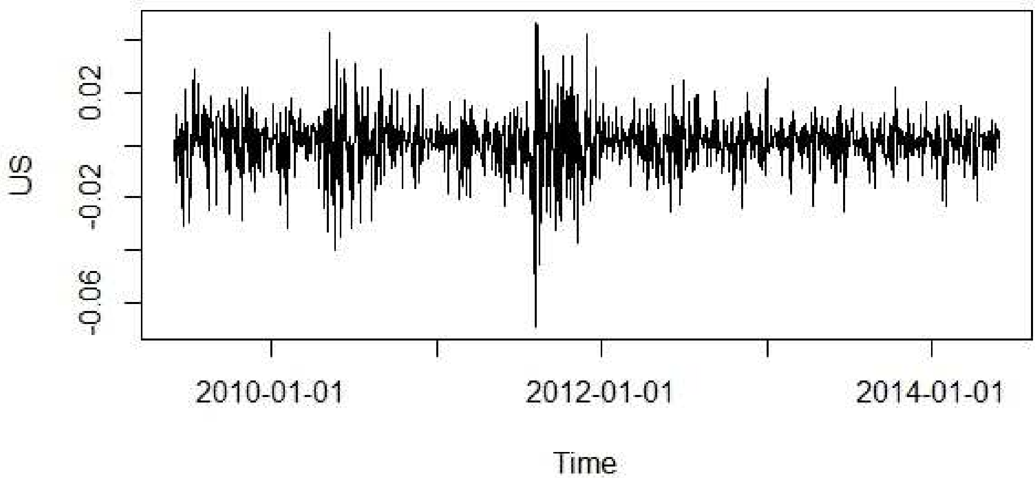

Figure 18 Returns of Canada S&P/TSX Composite Index (Eurozone Crisis)

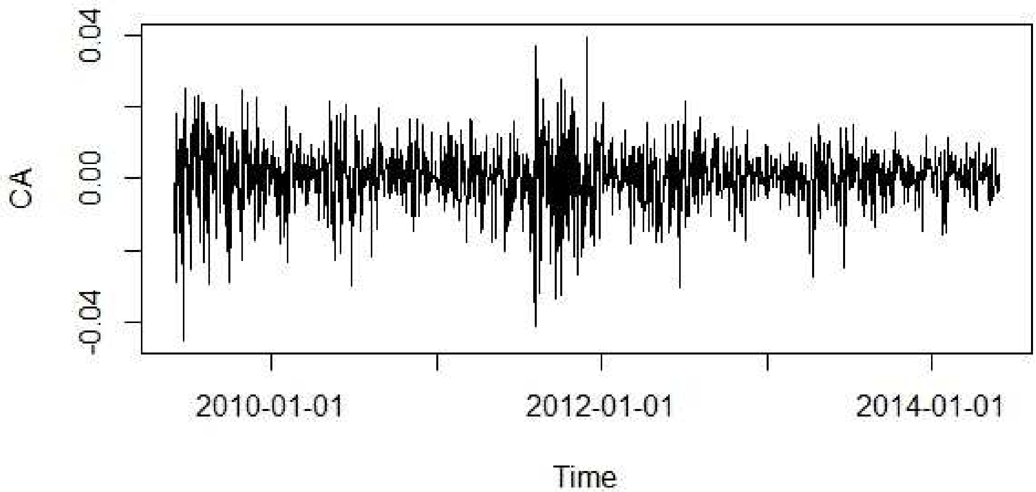

Figure 19 Returns of France CAC 40 (Eurozone Crisis)

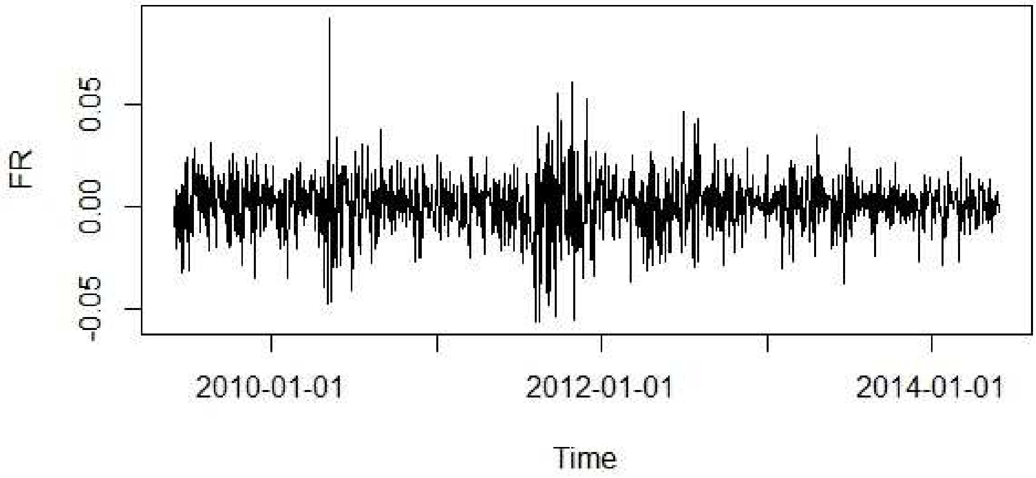

Figure 20 Returns of Germany DAX (Eurozone Crisis)

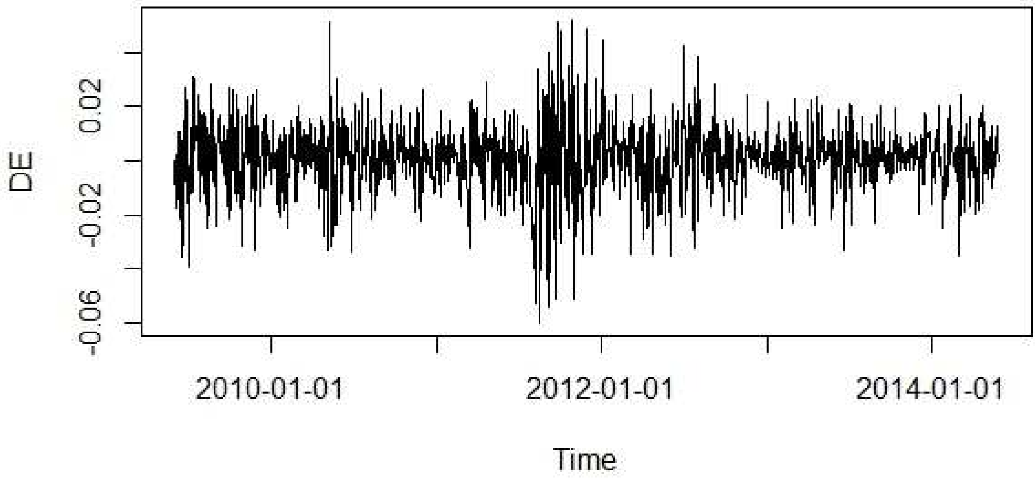

Figure 21 Returns of Italy FTSE MIB (Eurozone Crisis)

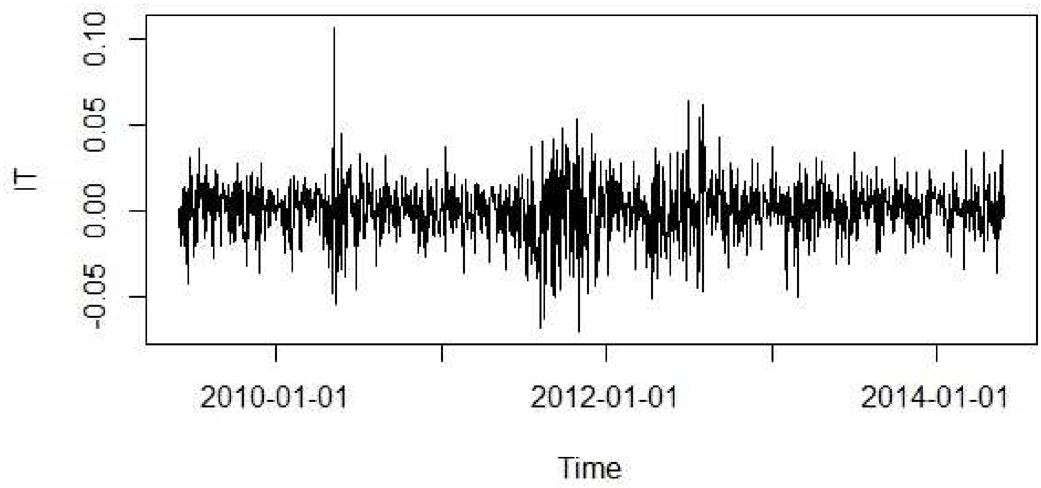

Figure 22 Returns of Japan Nikkei 225 (Eurozone Crisis)

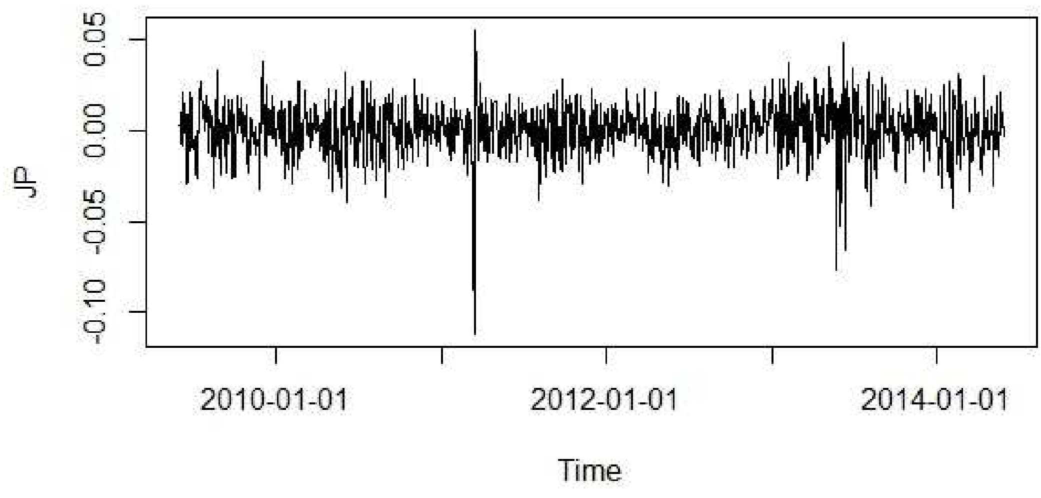

Figure 23 Returns of Brazil Ibovespa (Eurozone Crisis)

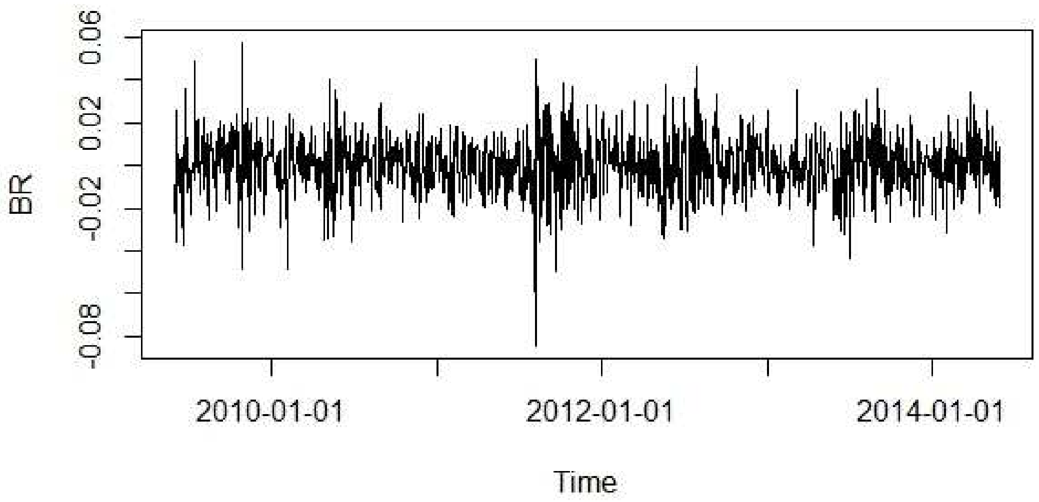

Figure 24 Returns of China SSE Composite Index (Eurozone Crisis)

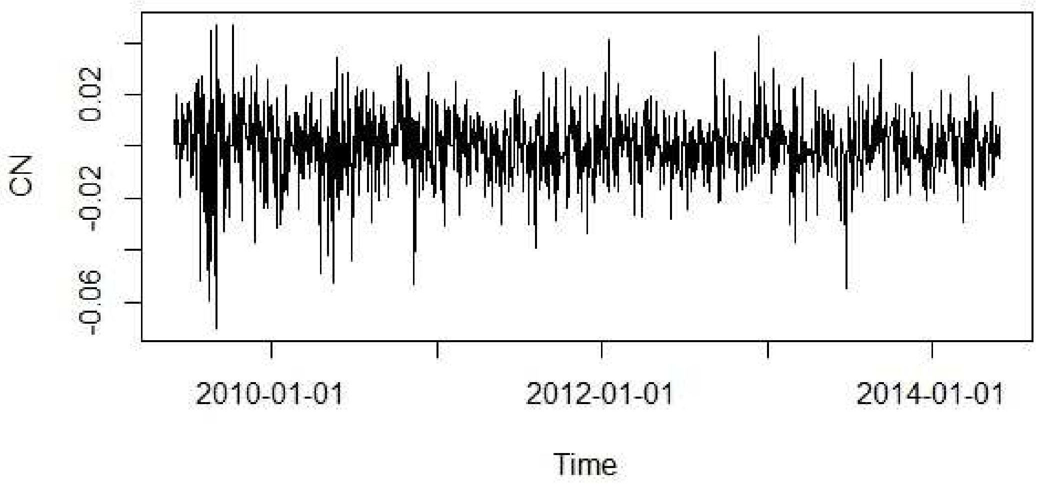

Figure 25 Returns of India BSE SENSEX (Eurozone Crisis)

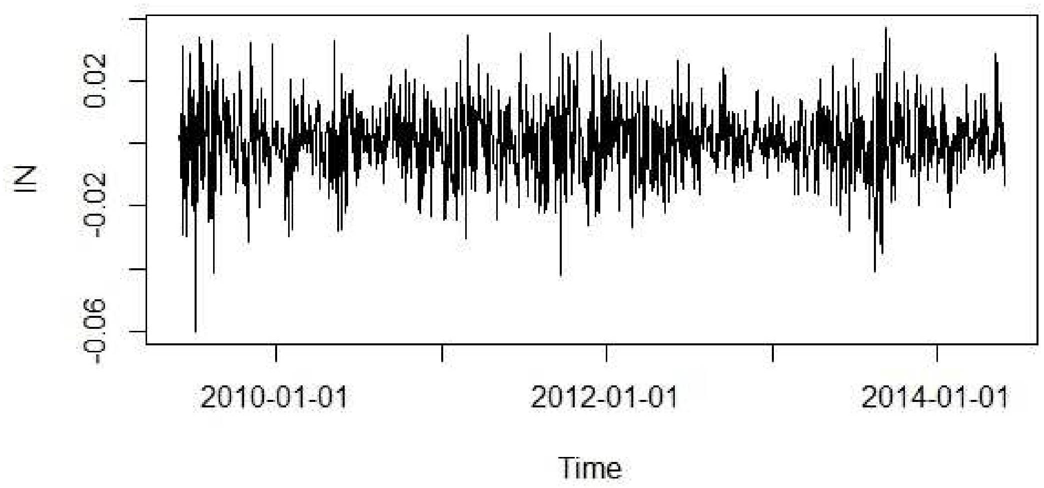

Figure 26 Returns of Russia RTS Index (Eurozone Crisis)

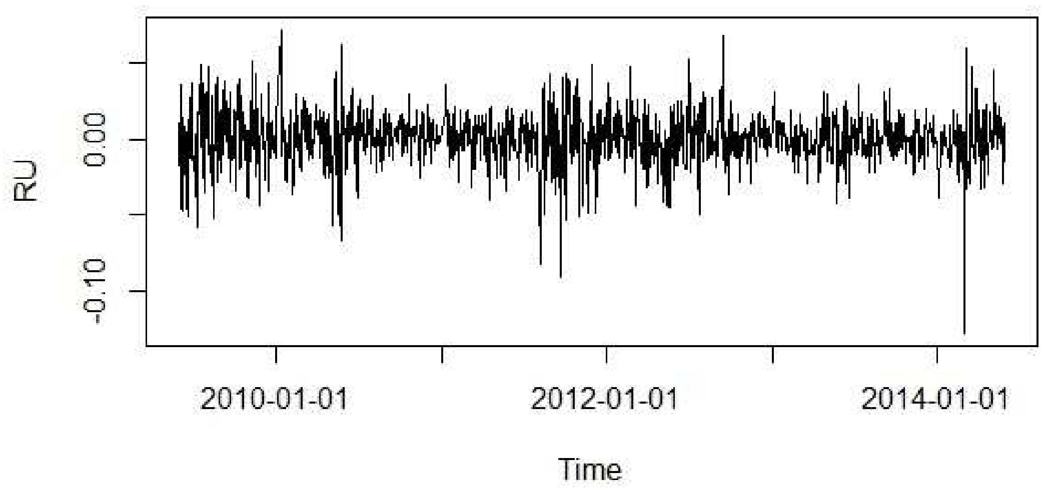

Figure 27 Returns of Spain IBEX 35 (Eurozone Crisis)

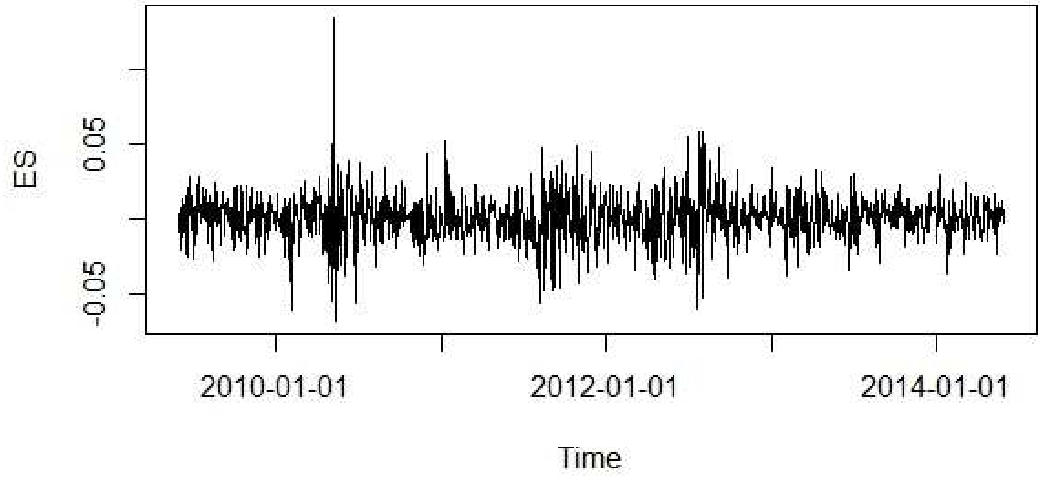

Figure 28 Returns of Portugal PSI Geral (Eurozone Crisis)

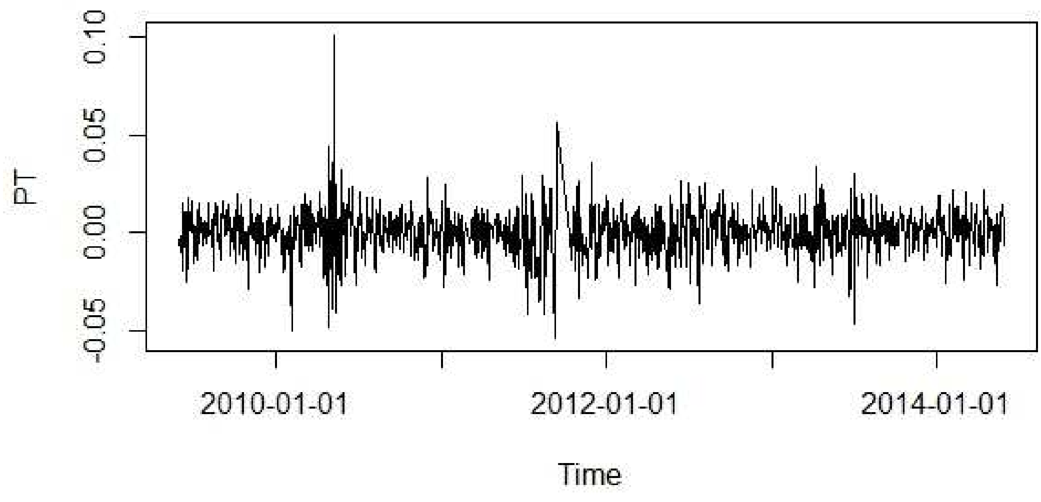

Figure 29 Returns of Greece FTSE/ATHEX LARGE CA (Eurozone Crisis)

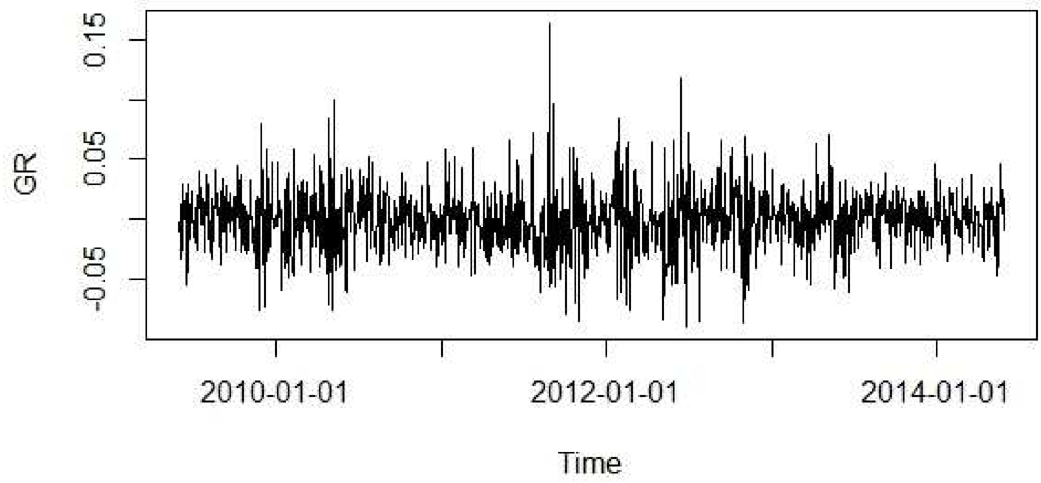

Figure 30 Returns of Ireland ISEQ Overall Price (Eurozone Crisis)

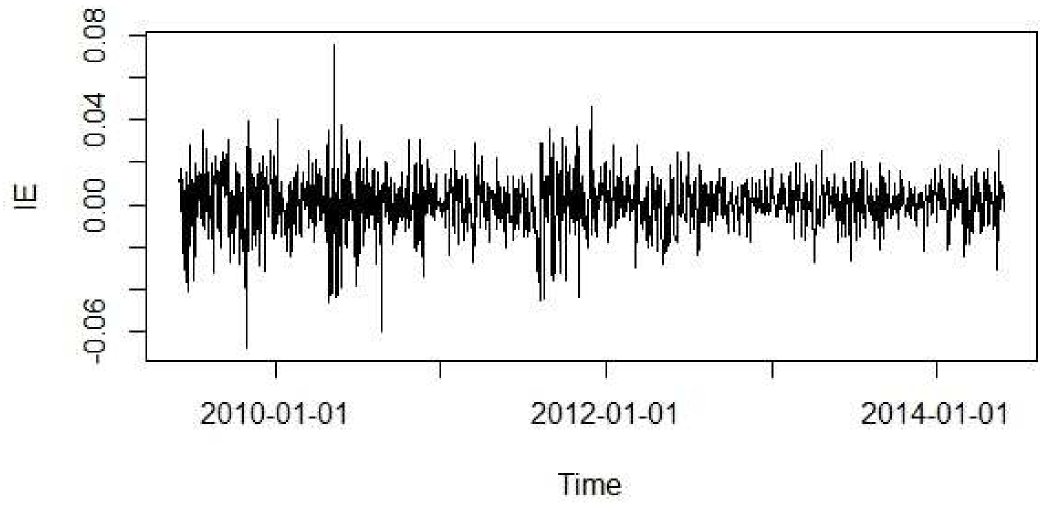

Figure 31 Stock Index of UK FTSE 100 (Asian Crisis)

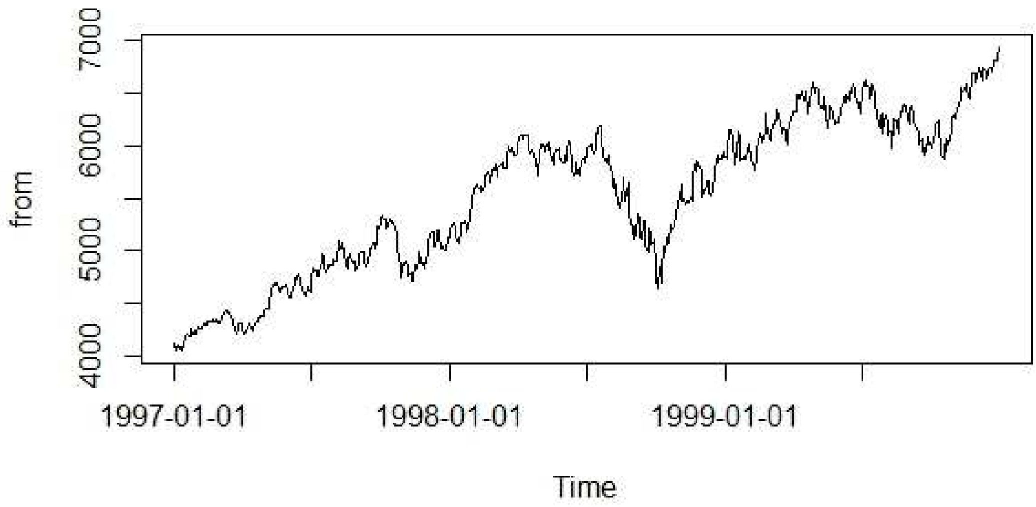

Figure 32 Stock Index of US Dow Jones Industrial Average (Asian Crisis)

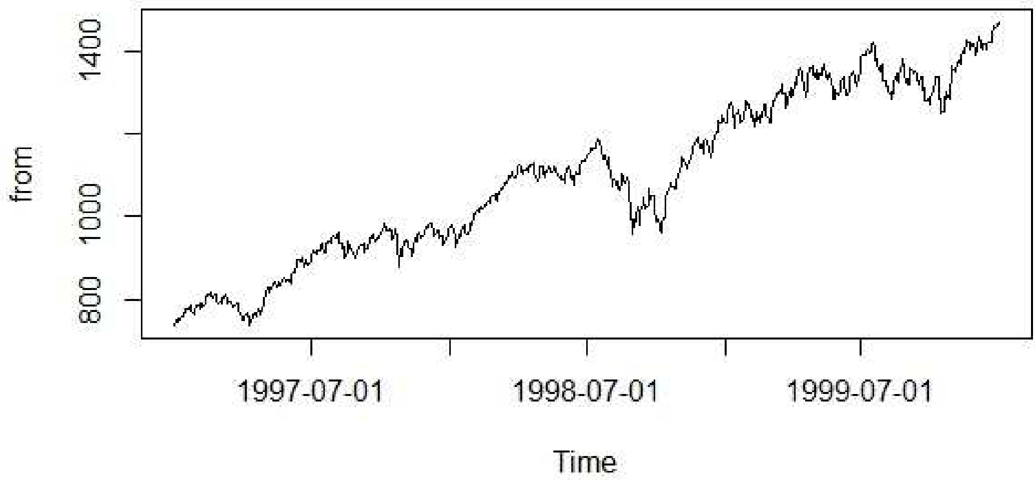

Figure 33 Stock Index of Canada S&P/TSX Composite Index (Asian Crisis)

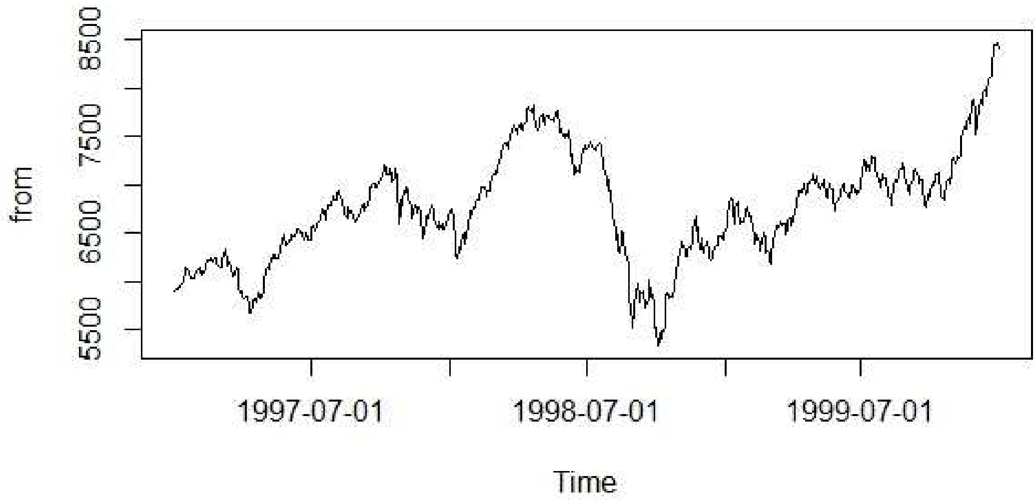

Figure 34 Stock Index of France CAC 40 (Asian Crisis)

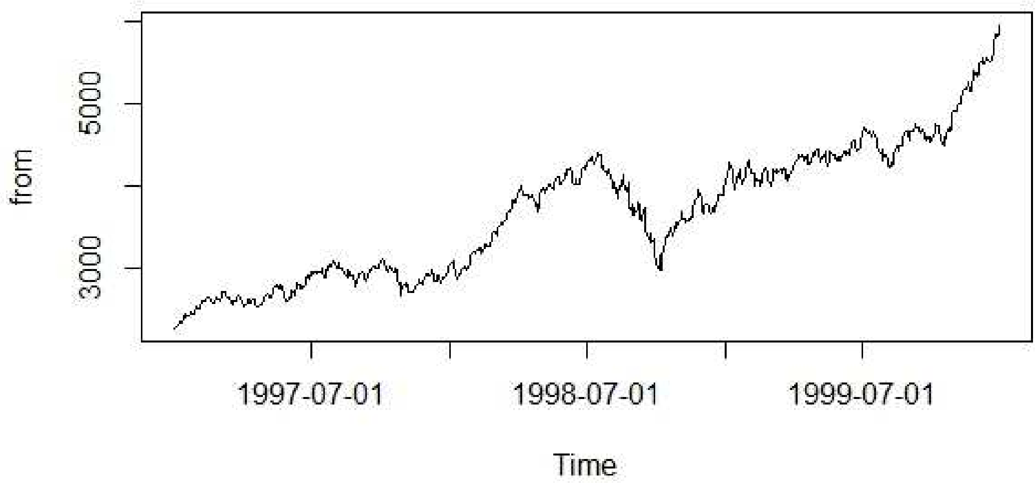

Figure 35 Stock Index of Germany DAX (Asian Crisis)

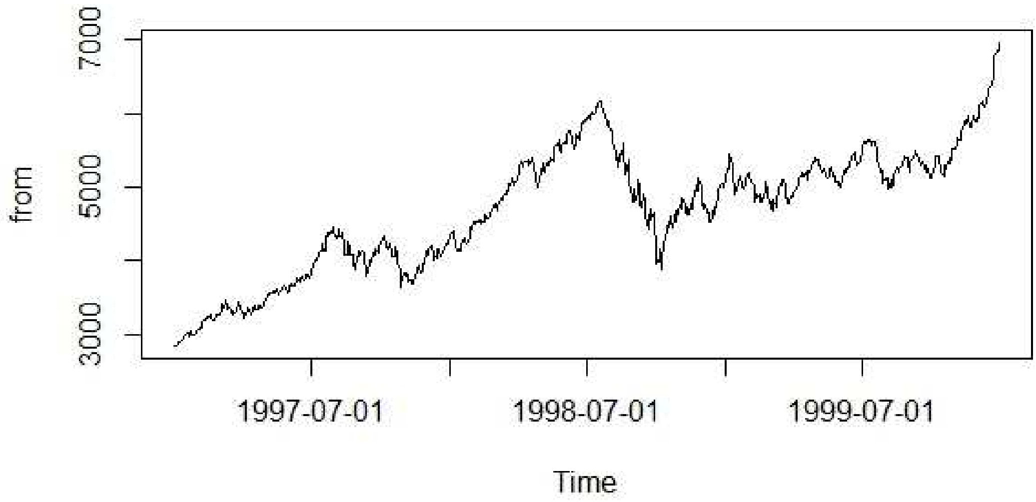

Figure 36 Stock Index of Italy FTSE MIB (Asian Crisis)

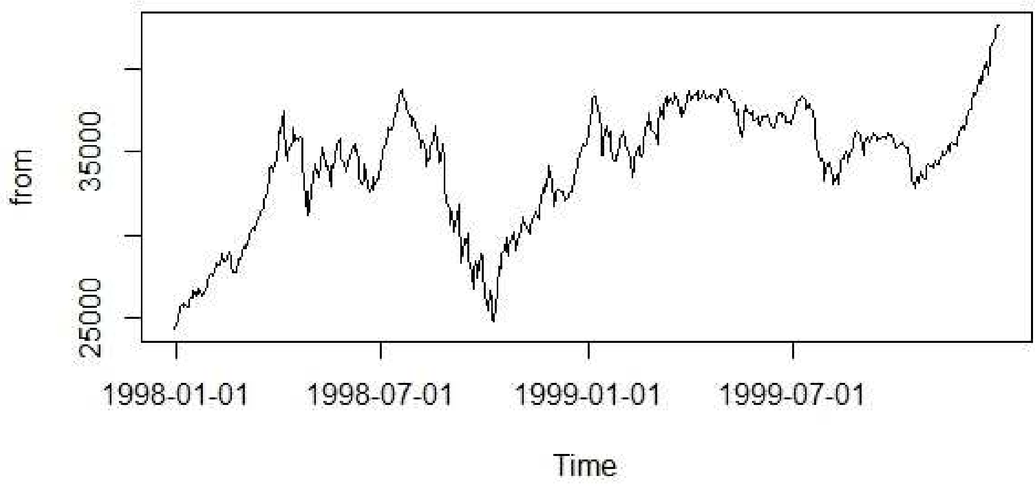

Figure 37 Stock Index of Japan Nikkei 225 (Asian Crisis)

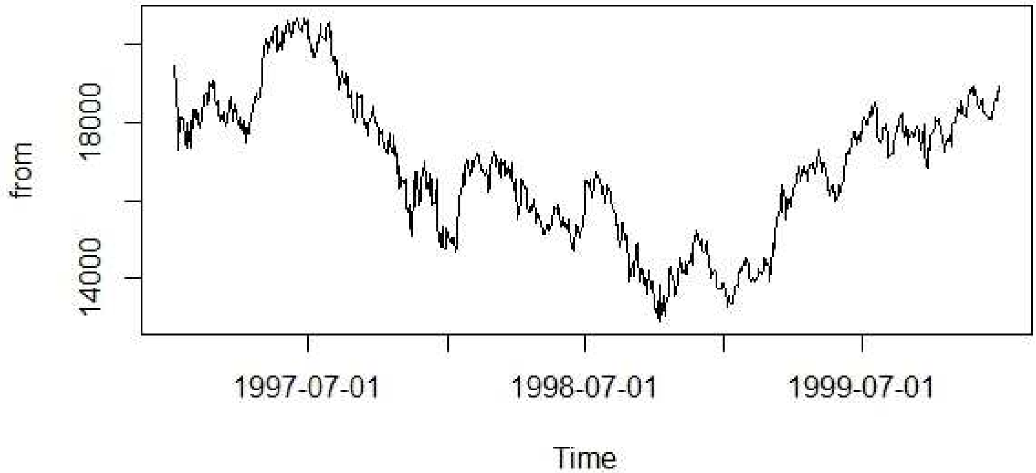

Figure 38 Stock Index of Brazil Ibovespa (Asian Crisis)

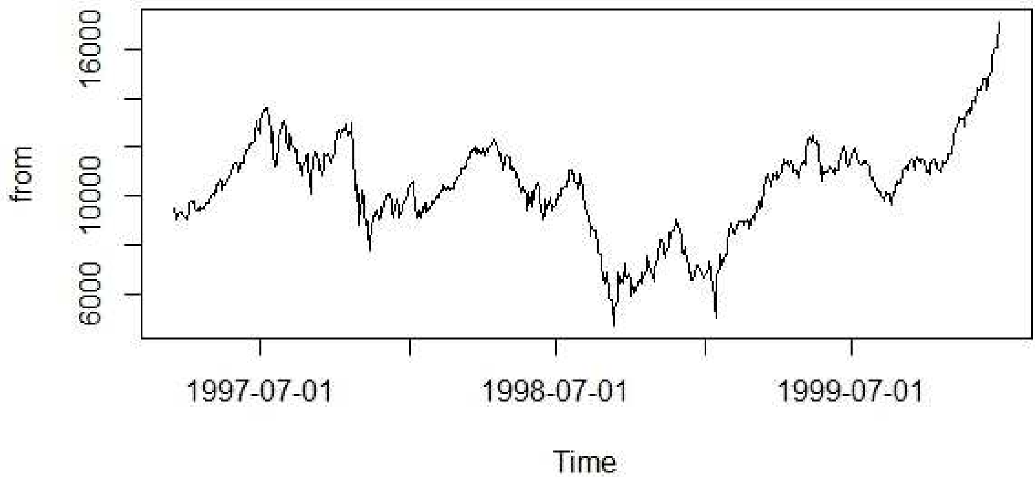

Figure 39 Stock Index of China SSE Composite Index (Asian Crisis)

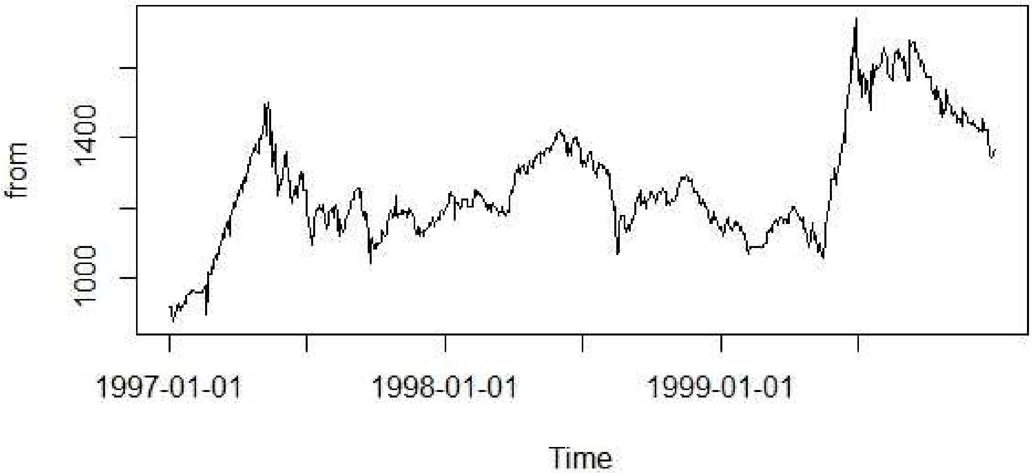

Figure 40 Stock Index of India BSE SENSEX (Asian Crisis)

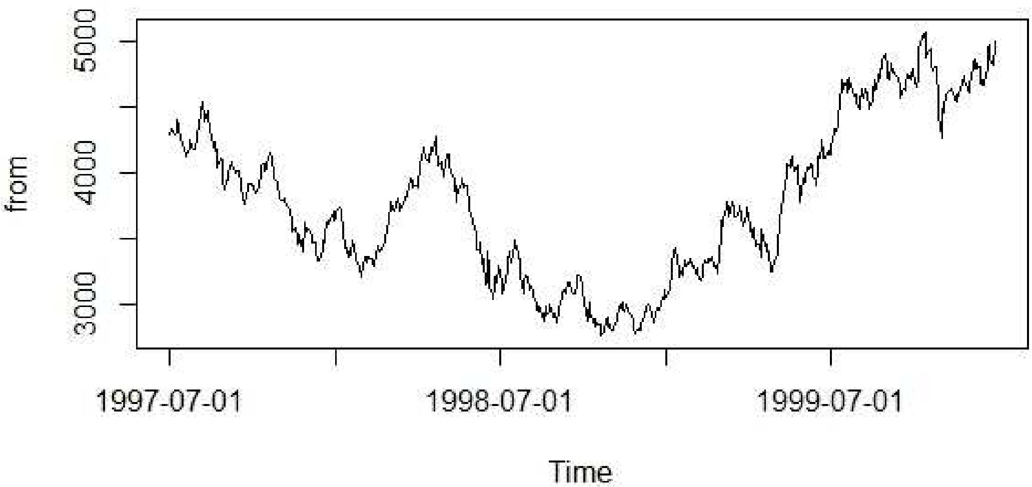

Figure 41 Stock Index of Russia RTS Index (Asian Crisis)

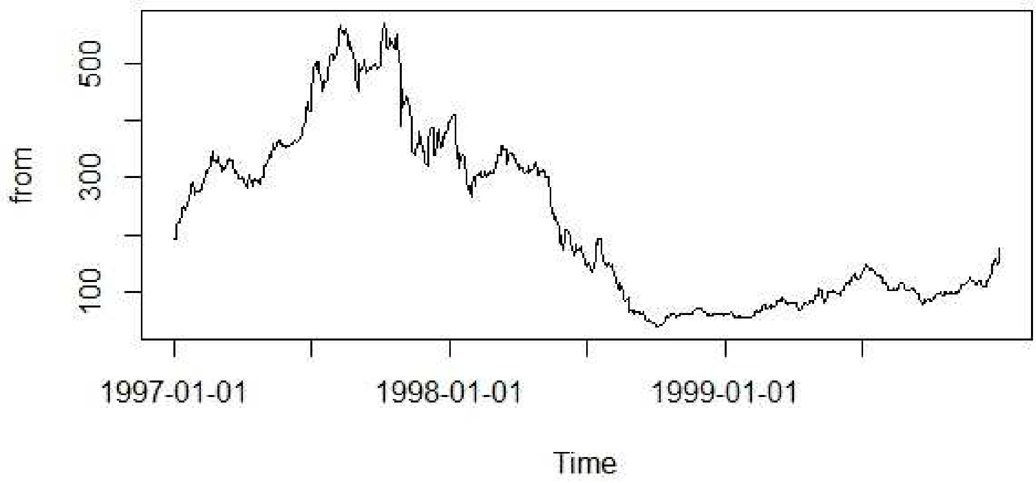

Figure 42 Stock Index of Indonesia JSX Composite (Asian Crisis)

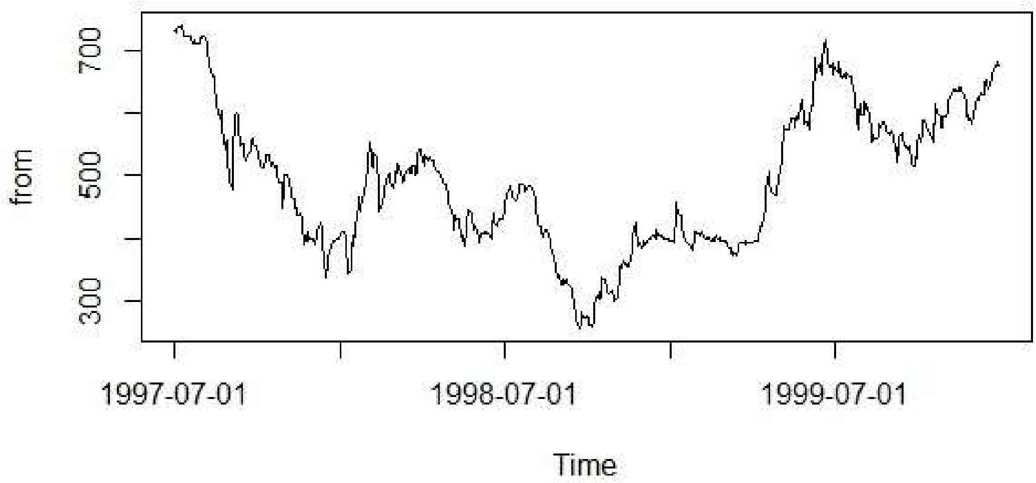

Figure 43 Stock Index of South Korea KOSPI (Asian Crisis)

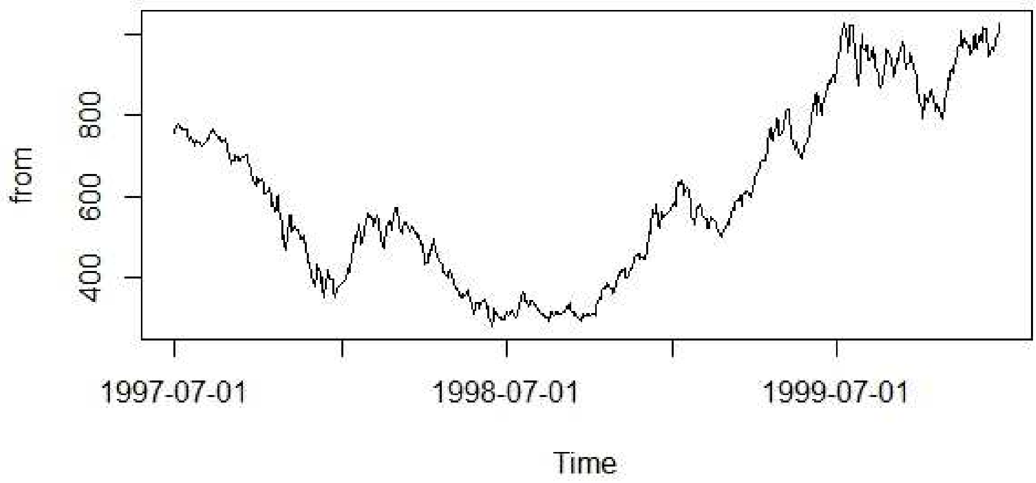

Figure 44 Stock Index of Thailand SET Index (Asian Crisis)

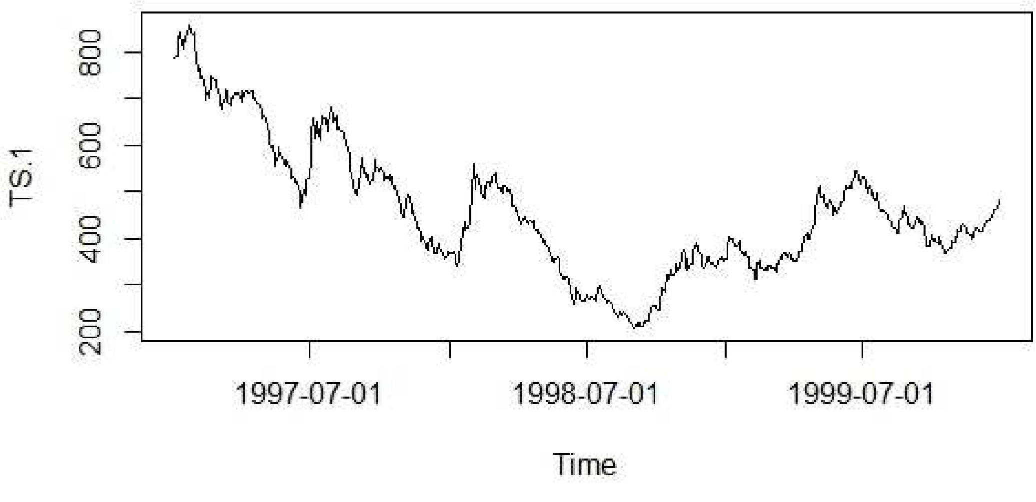

Figure 45 Returns of UK FTSE 100 (Asian Crisis)

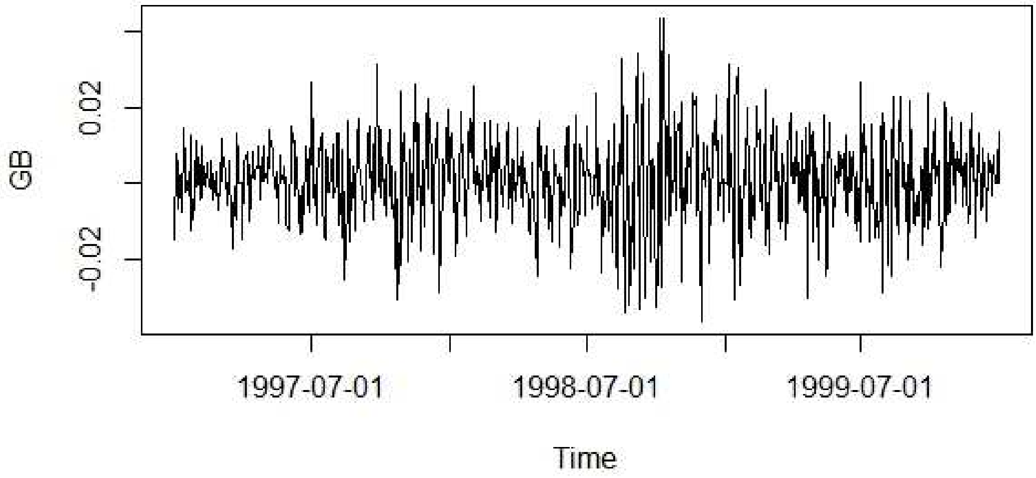

Figure 46 Returns of US Dow Jones Industrial Average (Asian Crisis)

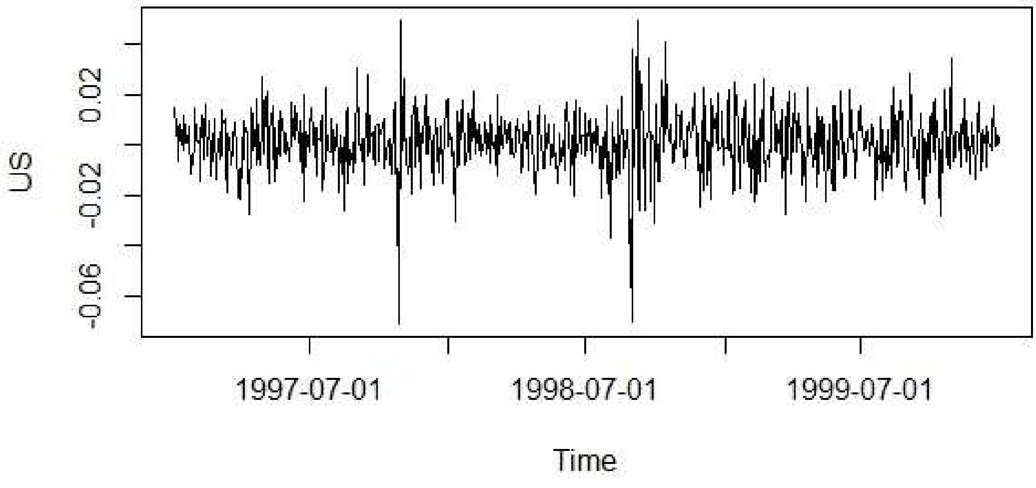

Figure 47 Returns of Canada S&P/TSX Composite Index (Asian Crisis)

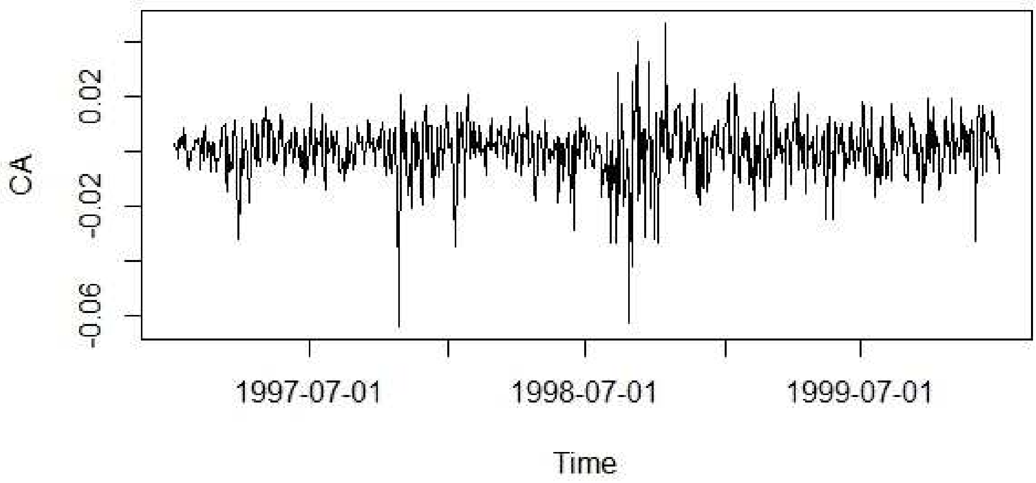

Figure 48 Returns of France CAC 40 (Asian Crisis)

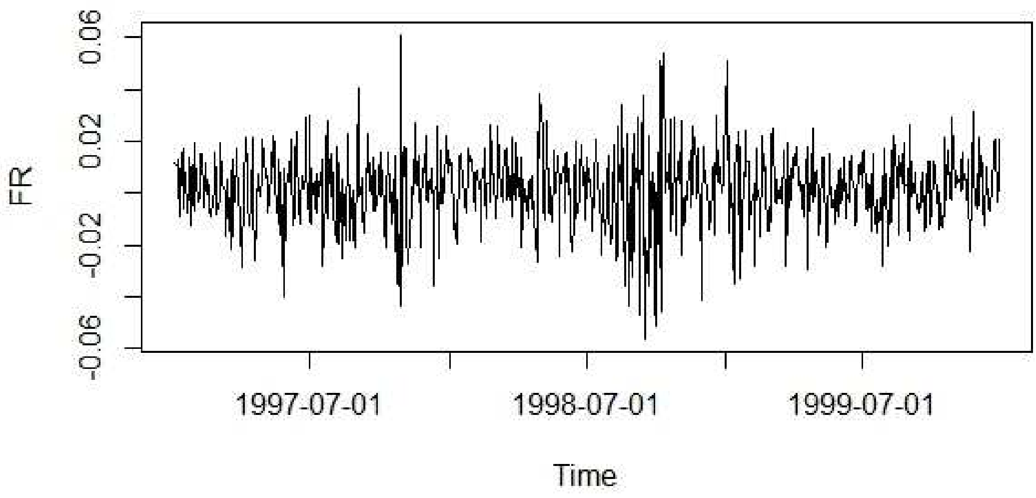

Figure 49 Returns of Germany DAX (Asian Crisis)

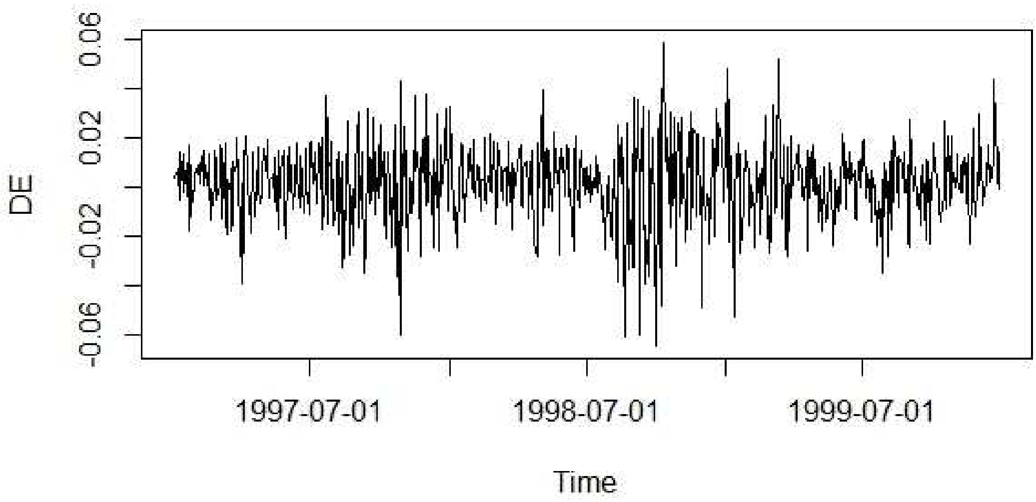

Figure 50 Returns of Italy FTSE MIB (Asian Crisis)

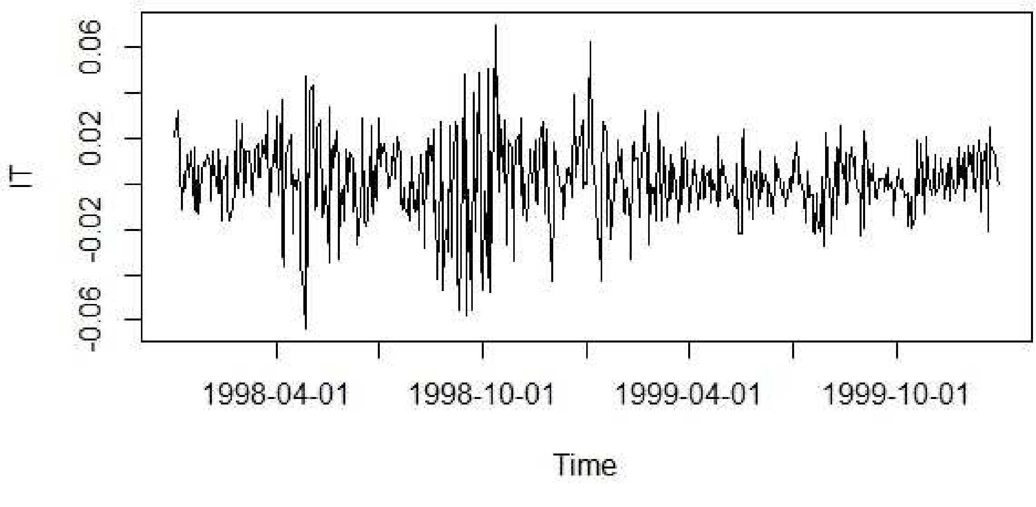

Figure 51 Returns of Japan Nikkei 225 (Asian Crisis)

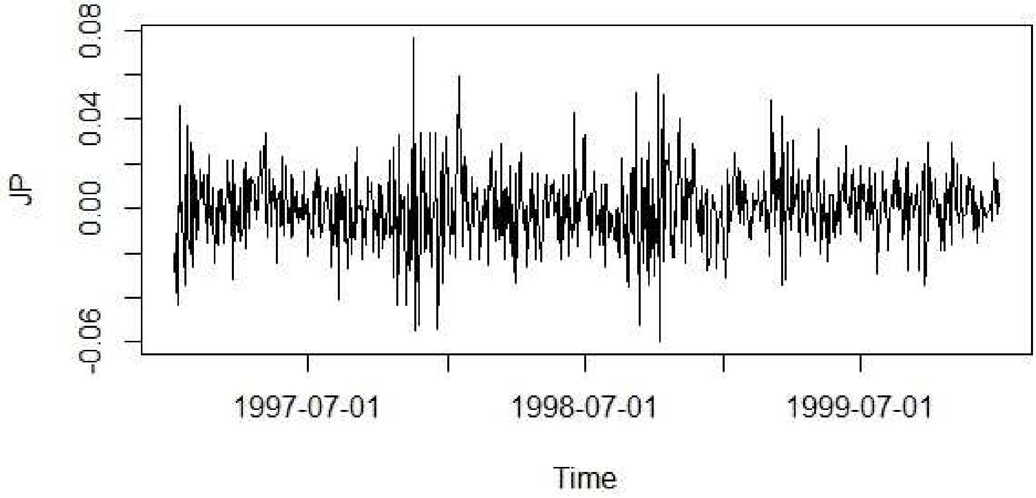

Figure 52 Returns of Brazil Ibovespa (Asian Crisis)

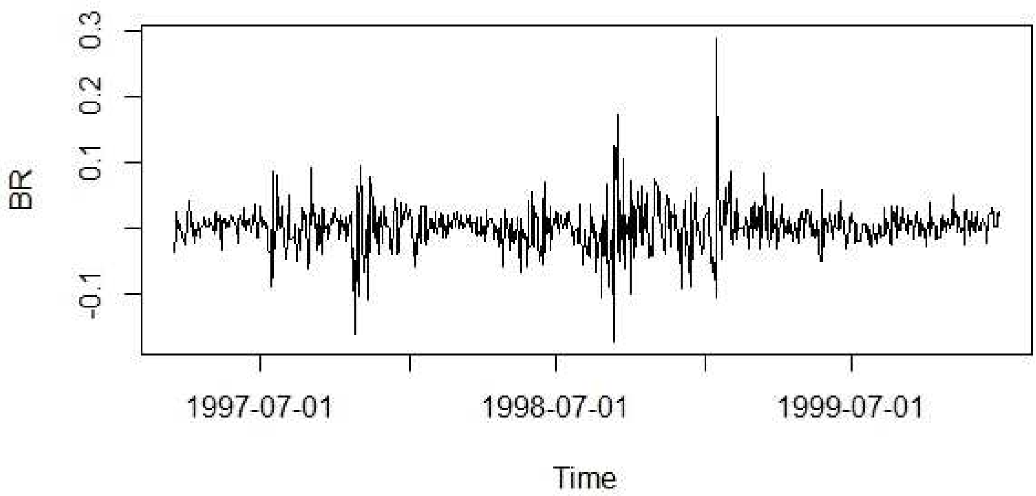

Figure 53 Returns of China SSE Composite Index (Asian Crisis)

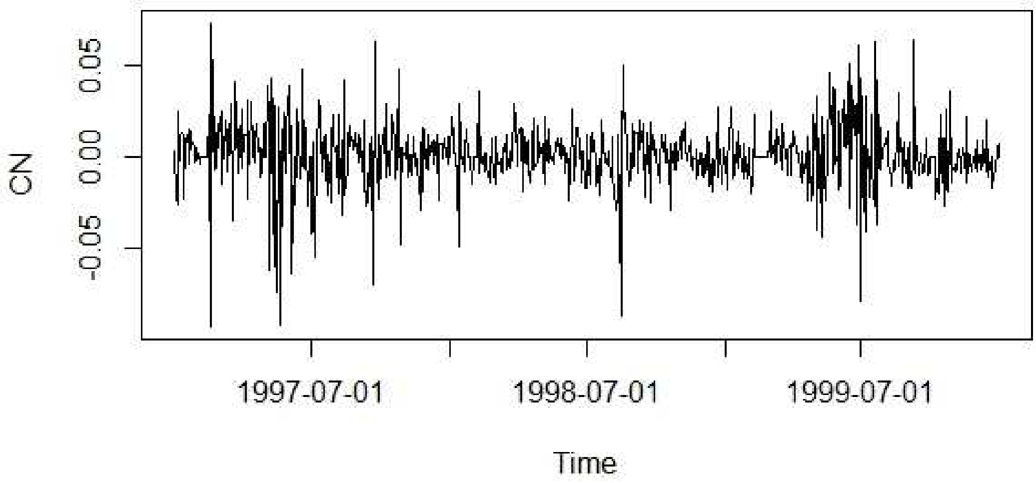

Figure 54 Returns of India BSE SENSEX (Asian Crisis)

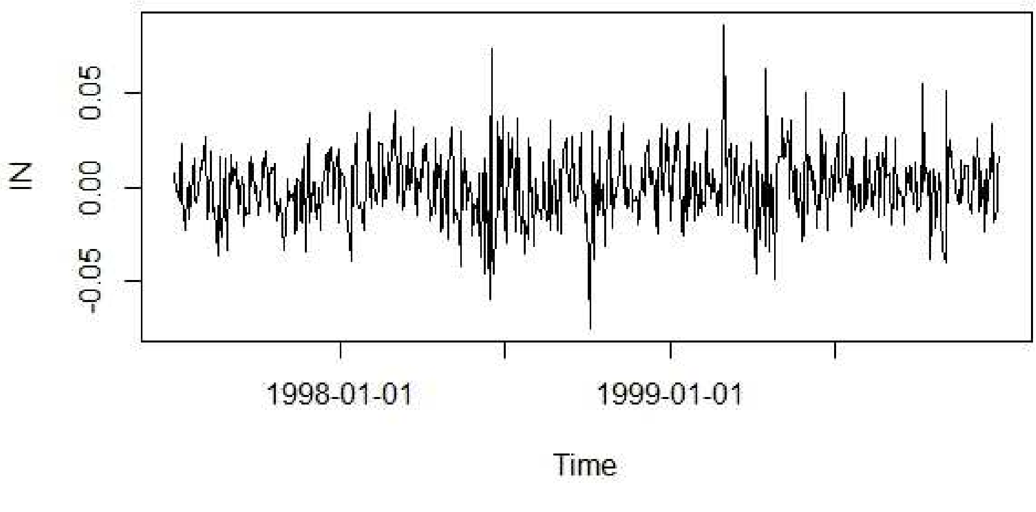

Figure 55 Returns of Russia RTS Index (Asian Crisis)

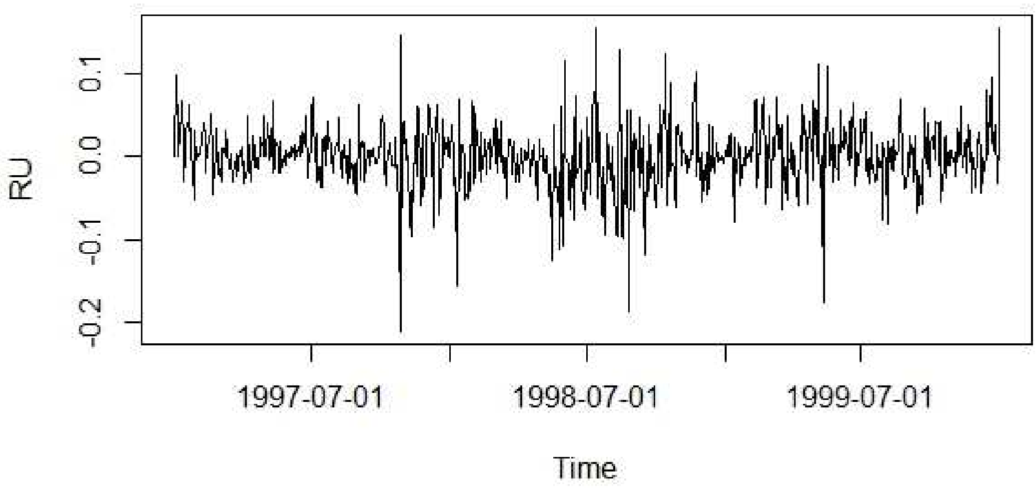

Figure 56 Returns of Indonesia JSX Composite (Asian Crisis)

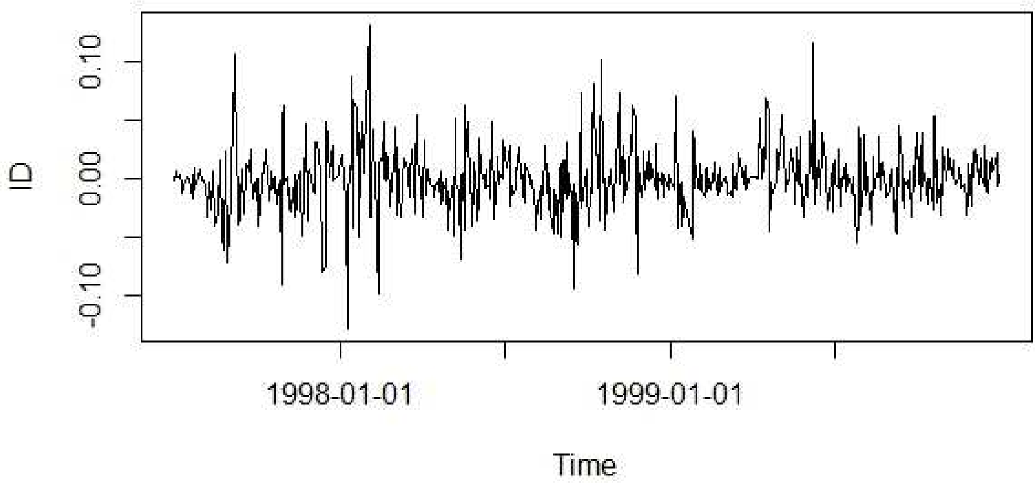

Figure 57 Returns of South Korea KOSPI (Asian Crisis)

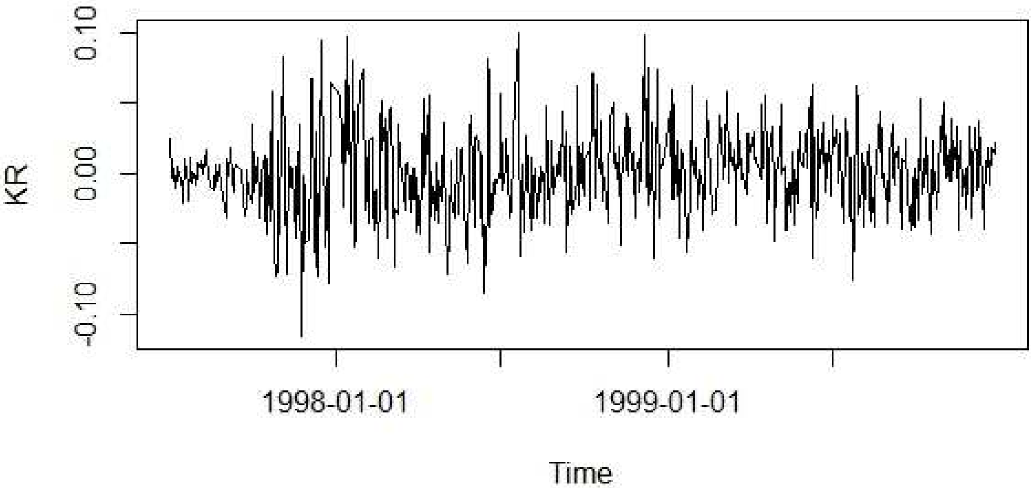

Figure 58 Returns of Thailand SET Index (Asian Crisis)